Trends in income inequality: a critical examination of the evidence in WIID2[1]

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1 Introduction

A combination of an increased theoretical interest in distributional issues and the increasing availability of data on income distribution has resulted in a growing number of empirical studies that examine different aspects of inequality. Typically these studies use compilations of inequality indices made by others. In an influential paper, Atkinson and Brandolini (2001) discuss the problems with data quality and consistency in both cross-country and within-country research that are especially pertinent when using secondary data sets on inequality. These problems are clearly present and may be the root cause of many controversies in social science research that involves economic inequality.

The problems of finding robust evidence on trends in within-country inequality – the topic of this paper – are, for example, highlighted by the estimates of world income distribution by Milanovic (2002*b*) and Sala-i-Martin (2002*a*). Both of these papers make use of a between-country component – measured as the inequality of mean per capita income between countries – and a within-country component – measured as an aggregate of income inequality within countries. It is largely the trend in the within-country component that pose problems. The authors make use of different types of data that are treated differently, which leads them to opposite conclusions about the direction of world income inequality change. Similar problems are to be found when looking at the effect of inequality on economic growth. Since estimates of within-country inequality often suffer from measurement errors, it casts doubt on the outcomes.

This paper examines changes across time in within-country inequality using the most recent, and we would argue, the most appropriate data at hand, the updated World Income Inequality Database (WIID2). We attempt to find whether it is possible to find robust evidence on inequality trends. Our empirical approach is to use so-called mixed-effects models with quintile groups means as the dependent variable, observed covariates as explanatory variables and allow for (at the most detailed level) country-specific intercepts and trends. This statistical framework allows us to assess in a structured fashion the actual patterns of inequality change across the world and to start to examine if these changes can be accounted for by readily observable economic and demographic factors.

This paper is structured as follows. We review earlier related studies on inequality trends and studies using secondary sources to examine maters related to income inequality in Section 2. We naturally focus on the use of within-country changes in this literature. In Section 3, we describe the structure of the most recent update of the WIDER Income Inequality Database (WIID) version 2.0, which provides the data we use here. Our examination of within-county trends is conducted in Section 4 and in Section 5 we offer a few concluding comments.

2 Literature review

2.1 Trends in the world income inequality

What one ideally would like to do when measuring world income inequality, is to account for both between- and within-country inequality, an exercise that until recently has been complicated to carry out. Due to the unavailability of data on within-country inequality for a sufficient number of countries and years, the income inequality among all the persons on earth is in several earlier studies estimated using only the between-countries component. In other words, every individual in a country has been assigned the country's mean income. Some studies give each country the same weight, while others weigh the country by its relative population size. On the other hand, more recent studies, such as Milanovic (2002*b*,*a*), Bourguignon and Morrisson (2002) and Sala-i-Martin (2002*a*,*b*), use in their examination of global inequality both between- and within-country inequality.

We have already noted that reliable data on within-country inequality and in particular within-country trends can be hard to come by. The above-mentioned studies seek in different ways to overcome this complication. Essentially one needs three different set of variables to derive the world income distribution: the evolution of mean income for each country, the trends in income distribution between all individuals within each country and the population sizes of each country. In Milanovic (2002*b*,*a*) both income shares, estimating the income distribution, and mean income/expenditures are taken from survey data whereas Bourguignon and Morrisson (2002) and Sala-i-Martin (2002*a*,*b*) rely on survey data for the shares but GDP data for the means. In the following we take a closer look at these approaches employed.

We start with Bourguignon and Morrisson (2002) who study the distribution of well-being of the world citizens during the last two centuries (1820-1992). As their study covers the longest period, their data sources are therefore likely the least accurate of those examined here.[1] . The estimation

[1] The study does not only focus on income distribution but also looks at life expectancy.

relies on real GDP per capita, expressed in constant PPP dollars, and the distribution of income is summarized by decile group shares and the two top ventile shares. The world distribution is obtained assuming that each quantile group in a country is made up of individuals with identical incomes. GDP per capita is assembled for 33 countries or groups of countries. Large countries, such as China, India, Italy and US, whose weight in the world is significant, are considered individually.

The data sources for income distribution in the 33 groups differ by period under analysis. The data are generally size-weighted disposable household income per capita. For the post-World War II period, income distribution data are an updated version of those in Berry et al. (1991). For the pre-World war II period, data for advanced countries are from existing historical series and have been adapted to fit the decile/ventile definition.

Distribution data are available or can be estimated for a few years prior to 1950 for a couple of countries. For the remaining countries and country groups, the distribution was arbitrarily assumed to be the same as in a similar country for which some evidence was available for the appropriate period. The estimations show that the inequality of the world distribution for income increased from the early 19th century up until World War II, after which it seems to have stabilized or at least to have increased at a slower pace. The rise in inequality for the entire period, estimated to be 39 percent when measured by the Gini coefficient and 60 percent when measured by the Theil index, is found to be robust with respect to measurement errors. The rise in inequality was mainly due to a dramatic increase in inequality across countries.

Sala-i-Martin (2002*a*,*b*) investigates in two similar papers the world distribution of income between 1970 and 1998 using aggregate GDP data and within-country income shares. The worldwide distribution of income is estimated using kernel densities, which in turn are used to generate world poverty rates and inequality indices. The data covers 125 countries or around 90 percent of the world population. PPP-adjusted GDP data are used in place of average income, while survey data are used to estimate the income shares. The within-country income group shares stem from Deininger and Squire (1996) and the World Development Indicators of the World Bank.[2]

Sala-i-Martin (2002*a*,*b*) classifies countries into three groups according to data availability. The first group, which consists of 68 countries and has 88 percent of the population that is included, has

[2] Sala-i-Martin acknowledges the critic of the Deininger and Squire data by Atkinson and Brandolini (2001) but claims that since most of the movements in global inequality stem form cross-country disparities rather than within-country ones, the main conclusion and trends will not change.

estimates of income shares available for several years (we were unable to glean from the papers the number of data points per country or other country-level details). For this group, the income shares are regressed over time to get a linear trend for each country. For the second group of 29 countries, income shares for only one year are available and for this group the income shares are assumed to be constant over time. For the remaining 28 countries, no share data are available so all citizens in these countries are treated as having the per capita income of the country.

The difference between the two papers Sala-i-Martin is how the income shares then are treated. In Sala-i-Martin (2002*a*), each quintile group is assigned a different level of income and within each quintile each individual is assumed to have the same level of income. Sala-i-Martin (2002*b*) goes a step further, and instead of assuming that incomes within quintiles are constant, each individual is assigned a different income using density functions. The underlying data are in both papers are the same. The first estimates kernel densities based on quintiles and the second decomposes the kernel density-based quintiles into kernels with 100 centiles.

All estimated inequality indices suggest global income inequality declined between 1980 and 1998. Most of the global disparities can be accounted for by between-country inequality. The estimated reductions in inequality are mainly driven by income increases in China, the world's most populous country. The process is reinforced by the positive growth performance of India. Even if inequality has increased in China and India, the inequality increases have not been nearly large enough to offset the substantial decline in across country disparities. The difference in the results between the two different papers is not substantial, the level of inequality is only a little higher in the second. In the latter paper, within-country inequality's contribution to global inequality is around 35 percent (for the mean log deviation and Theil indices), whereas in the first it was about 30 percent. The exact proportion varies across time – in 1970 only 20 percent of the world inequality was accounted for by within-country inequality.

Milanovic (2002*a*) is highly critical of Sala-i-Martin (2002*a*,*b*), claiming that these result not in the distribution of income among world citizens, but in a population weighted international income distribution of income, augmented by a constant shift parameter. According to this view, the calculations essentially boil down to assuming within-country inequality to be fixed throughout the entire period. This is because fitting the distributions based on very fragmentary data plus the extrapolations in time empties out almost all of the variability from the within-country component.

Two specific problems are pointed out by Milanovic: too few data (quintiles) to derive a distribution and the absence of data for most of the years so that missing data have been filled in by extrapolations. To derive the entire distribution based on but a few data points lead according to Milanovic (2002*a*) to a very large degree of error. Income quintile group shares exhibit in many countries substantial variability, rather than following the linear trends both forward and backward that Sala-i-Martin forces them to do. When doing a linear approximation, the n-th quintile group share in year t influences the linear approximation of that and all quintile group shares in all other years for which one does extrapolations.

According to Milanovic, the average number of observations in the first two groups for which Sala-i-Martin has observations is 5.5 out of 27 years from the Deininger and Squire data. Since no data are available for the third group, the overall time coverage is only 15.5 percent. Only 6 countries have observations for at least 2/3 of the time. The fact that Russia and all other countries of the former Soviet Union are excluded, despite the availability of data, is also a drawback, since these countries lately have experienced high increases in within-country inequality. In Milanovic's own calculations, the transition countries account for about a half of the 2.8 Gini increase of world inequality that he finds between 1988 and 1993. If one would increase Sala-i-Martins Gini with 1.5 Gini points from 1990, it would not show a downward trend but remain stable.

Milanovic (2002*b*) estimates the world income or expenditure inequality for individuals for the years 1988 and 1993, and in later studies also for 1998. The world distribution is essentially derived in the same way as one would derive a country's income distribution from regional distributions. Household surveys from 91 different countries adjusted for difference in PPP are used. Unit record data are available for about 3/4 of the reported observations. For the rest, mean income or expenditure per decile or any other population group share (in a few cases also quintile group shares) are used from grouped data.

The data sources include the Luxembourg Income Study, World Bank LSMS surveys, various other World Bank sources, Central Statistical Offices and research studies. In the cases where individual data have been available, Milanovic has sought to define the income variable in as consistent a fashion as possible, not only including monetary incomes but also home consumption. In the rest of the cases predefined definitions are used. The unit of analysis is always individuals ranked by their household per capita income or expenditure. The data cover 84 percent of the world population and 93-94 percent of the current dollar GDP.

The most problematic continent is Africa, for which a bit less than 50 percent of the population is covered for both of the years studied. The Western countries are almost completely covered whereas Asia, Eastern Europe and former Soviet Union are covered to 90 percent and Latin America to 95 percent. China, India, Bangladesh and Indonesia have been divided into urban and rural parts that are treated as separate countries.

The problems in the study, as pointed out by Milanovic, relate largely to the within-country estimates as the surveys lying behind the estimates are not necessarily very comparable and based on both expenditure and income data. The resource concepts are mixed, since separate distributions for income and expenditures would result in a big and unevenly distributed drop in the number of countries observed. Namely, most African and many Asian countries conduct expenditure surveys, but in much of the rest of the world, income surveys are relied on. The regional spread of the surveys is also a problem when the surveys are mixed, since expenditure surveys in general yield lower estimated inequality and a higher estimated average, which will result in a downward-biased Gini coefficient.

Milanovic (2002*b*) finds that world economic inequality, measured by the Gini coefficient, increased from 0.63 in 1988 to 0.66 in 1993. The increase is driven primarily by differences in mean income between countries than inequalities within countries. The within-country component accounts only for 12-25 percent of the inequality depending on the index used. The greatest contributors to the world Gini are large countries that are at the two poles of the income distribution spectrum. One pole is represented by more than 2.4 billion people living in rural and urban India, Indonesia and rural China, the other by the 1/2 billion people living in large OECD countries.

Thus, differences in ways of dealing with incomplete data are at least in part responsible for two opposing and influential views of what is happening to global inequality.

2.2 Studies on the relationship between income distribution and growth

Apart from in studies on the world distribution on income, within-country inequality has also been introduced into studies on the economic performance of countries. These studies have been inspired in part by developments in theories of endogenous growth (see e.g. Aghion et al., 1999) that let inequality affect economic growth through political economy mechanisms or capital market imperfections. The impact of income inequality on growth has been investigated in several cross-sectional and a few panel studies. In this paper, we are most interested in the studies that use panel data, since changes in within-country inequality is what drives fixed-effects type panel studies.

The typical cross-sectional study involves "Barro-type" regressions. Typically, the average annual rate of growth in per capita GDP over a period of 25 years is regressed on a set of explanatory variables, including some index of income inequality in order to assess their relative contribution to growth.[3]. The impact of inequality on growth is quite consistently found to be negative. This consistency is not very surprising, since the studies use very similar methods and data. The cross-sectional studies have been criticized for their *ad hoc* specifications and for the fragility of many of the results. Since these regressions typically assume no measurement errors in the explanatory variables, and inequality in general is subject to severe measurement errors, the validity of the results can be questioned. The reasons why cross-sectional studies have been carried out despite of their drawbacks have probably a lot to do with the lack of data. The authors have tested their theoretical models with the limited data that have been available.

From a theoretical perspective, the problem with cross-sectional studies is that they are compatible with the assumption of single representative economies, which is empirically problematic as economies in the real world can hardly be meaningfully considered representative. Countries differ in population size, per capita incomes, institutional arrangements and degree of development only to name some. Dummy variables and variables indicating the level of development can handle some of the issues but the country specific effects will regardless be captured by the error term. The use of panel-data models is therefore more appropriate as they allow for country specific effects and therefore capture heterogeneity between countries and in addition gives the possibility to examine if the results hold for several periods. Instead of analyzing differences in inequality and growth across countries, fixed-effect panel models allow researchers to measure how *changes* in inequality are related to *changes* in growth within a given country (and of course to test if neglect of within-country fixed effects do, in fact, lead to biases in cross-sectional estimates).

One author who has made an attempt to use panel-data models is Forbes (2000), in an article challenging the belief that income inequality has a negative relationship with economic growth. She brings forward two potential econometric problems in the previous work: measurement error

[3]See, for example, Alesina and Rodrik (1994), Persson and Tabellini (1994), Perotti (1996), Deininger and Squire (1998). Aghion et al. (1999) surveys these studies.

and omitted variable-bias. To reduce omitted-variable bias, panel estimations are carried out and to reduce measurement errors, the Deiniger & Squire high-quality dataset is used. She believes that "*Deininger and Squires new dataset can not only minimize measurement errors in inequality and any resulting bias, but also can increase the efficiency of estimates*". She then uses a similar model as most empirical work on inequality and growth, estimating growth as a function of initial inequality, income, male and female human capital, market distortions, and country and period dummy variables. The endogeneity of the right hand variables, especially inequality, is dealt with using dynamic panel data estimators of the Arellano-Bond type. This estimation technique corrects not only for the bias introduced by the lagged endogenous variable (the income term), but also permits a certain degree of endogeneity in the other regressors (Forbes, 2000). Inequality is measured by the Gini coefficient. As Deininger and Squire recommends, 6.6 is added to the Gini coefficients based on expenditures.

The study focuses on growth for six periods between 1966 and 1995, averaging the growth over five year periods. Growth in period 3 is thus measured from 1976-1980 and is regressed on explanatory variables measured during period 2. In practice, each explanatory variable in period 2 is measured 1975, except inequality which is often not available on an annual basis and is taken from the year closest to 1975. Even if six periods of growth is estimated, countries with observations from at least two consecutive periods are included; this results in a sample consisting of 45 countries and 180 observations. The results of the study are different from earlier empirical studies in that inequality is found to have a significantly positive relationship with subsequent economic growth. This relationship is found to be highly robust across samples, variable definitions, and model specifications.

Problems in the study as brought up by Forbes herself are the limited number of observations, the regional coverage being far from representative as Sub-Saharan Africa is not represented and nearly half of the countries are from OECD, and finally that the Gini coefficient are not based on identical units of accounts since both income/expenditure definitions vary and both households and person based estimates are used.

A closer look at the data reveals this problem. Definitions are not only differing between but also within countries. For example, for Finland both LIS data and national sources are used. The estimates are based on household distributions and equalized distributions are mixed and as a result income inequality in Finland appears to have been jumping up and down over the years. For Sri Lanka and Spain, a mix between gross incomes and expenditures (with 6.6 added) are used and for Mexico and Venezuela household and person weighted data are mixed. More examples could be brought up but the above mentioned ones illustrate fairly well the problem.

Aghion et al. (1999), commenting on an earlier version of Forbes (2000), suggest that the Arellano-Bond generalized method of moments estimators result in excessively small standard errors when a small sample is used, casting doubts on the significance of her coefficients. They also point out that the assumed lag structure implying that inequality today affects growth in five years is ad hoc. When Forbes uses ten instead of five year periods, the coefficient on inequality remains positive but becomes insignificant, suggesting that that the periodization makes a difference.[4] Aghion et al. (1999) further point out that in order to obtain positive and significant coefficients, Forbes has to restrict the data on inequality to the high-quality dataset. However, as Aghion et al interpret the criticisms of the DS dataset, Atkinson and Brandolini (2001) suggest that the "high-quality" dataset of Deininger and Squire is not appropriately chosen and should therefore not be the basis for use in regression models.

2.3 Secondary data sources: criticisms

In an influential and critical paper on on the use of secondary data in studies of income distribution, Atkinson and Brandolini (2001) discuss the quality and consistency in income distribution data both within and across countries. They show how both levels and trends in distributional data can be affected by data choices. Within countries, consistent income distribution series over time do not necessarily even exist, or there may be several different sources or different definitions in use. As there is no agreed basis of definition, sources and methods might vary, especially across, but also within countries. This might be the case even if the data comes from the same source.

Atkinson and Brandolini especially warn against simply downloading the accept series in the Deininger and Squire dataset and treating it as a continuous series. The high-quality dataset only includes one observation per country and year, but these often come from different sources using different definitions. They show that if the variables are used in econometric work, the empirical findings can be significantly different depending on the data used. Differences in definitions are

[4] Because of the limited degrees of freedom available the result should however be interpreted with caution.

shown to be quantitatively so important that simple adjustments are not enough. For example, making a simple additive correction of 6.6 to the expenditure Ginis, Forbes (2000) induces a measurement error in the variable, instead of reducing it. Atkinson and Brandolini suggest that one should strive to use observations that are as fully consistent as possible.

3 The WIDER Income Inequality Database v 2.0

The data used in this paper is from the newly revised and updated World Income Inequality Database (WIID2), a secondary database published by UNU - World Institute for Development Economics Research with information on inequality in roughly 150 countries. WIID2 is built on the fully revised and cleaned data of WIID1, including the data of Deininger and Squire (1996), but has some new features, has updated the estimates as new data have become available and provides more extensive documentation. To make the database more user-friendly, overlapping estimates from the old database were deleted along with low-quality estimates for countries where high-quality estimates are available. WIID2 retains some data that might otherwise have been deleted if the estimates were from some of the big compilations of inequality data.[5] Important sources for the update were the new data gathered by Deininger and Squire 2004,[6] the unit record data of the Luxembourg Income Study[7] , the Transmonee data by UNICEF/ICDC, Central Statistical Offices and research studies. In addition to the Gini coefficient and income group share data with quintile/decile group shares, along with the income shares of the poorest 5 percent and richest 95 percent of the population, survey means and medians were included whenever available.

For the purpose of adding new estimates to the database and assessing the quality of existing ones, a preferred set of features was defined for the conceptual base and the underlying data. With the conceptual base we mean the definitions of income or consumption/expenditure, the statistical units to be adopted, the use of equivalence scales and weighting. The Canberra Group (2001; an

[5] Paukert (1973) and Jain (1975) are examples of these. To delete overlapping observations is against the recommendations of Atkinson and Brandolini (2001). Since such a large number of overlapping observations where present in WIID1 (mostly because of the overlap of observations collected by WIDER and those of Deininger and Squire) and some observations where from sources with no documentation, this was however felt to be the best solution in order not to make the database too confusing.

[6] This update is only published in WIID2 due to an agreement between the World Bank and WIDER to only publish one database. All the estimates are calculated by Kihoon Lee at the World Bank using unit record data only. The data are based on World Bank LSMS-surveys and other surveys either conducted in assistance of the World Bank or available in house.

[7] For more information please look at http://www.lisproject.org/

expert group on household income statistics) recommendations were largely followed concerning income concepts and unit issues, whereas Deaton and Zaidi (2002) recommendations on how to use consumption data for welfare measurement were used for the definition of consumption and expenditure. Table 1 summarizes the most preferred set of underlying concepts for the inequality estimates.

Estimates not following the preferred set of definitions were not automatically considered to be of bad quality, but when updates were made, the definitions were followed as far as possible. This was for example done when calculating estimates based on unit record data from the Luxembourg Income Study. Due to unavailability of observations using the preferred set of definitions, estimates based on other definitions were in several cases used. The differences appear especially in the statistical units and the weighting.

Concerning demands on the underlying data, a long list of desirable features could be pointed out but in practice mainly *coverage issues, questionnaires* and *data collection methodology* was paid attention to. In many cases the documentation available was hardly sufficient to even judge the three last mentioned issues. Concerning covering issues, national coverage is desirable and attention was also paid to the exclusion of some special groups such as households above a certain income threshold or households only living on charity. Questionnaires or diaries on their side need to have a sufficient level of income or expenditure detail to be acceptable. The data collection methodology is especially crucial for expenditure surveys and in countries where a large proportion of the population works in the informal sector with infrequent incomes, as too long recall period leads to considerable measurement errors. For expenditure surveys, diaries must be kept or in case of illiteracy, frequent visits must be made to the households. Expenditure surveys collected in one single interview or with long recall periods were not considered to be of acceptable quality.

We restrict interest here to the period 1960-2000 during which we have information from 115 countries and altogether 1585 data points. Full details of the data used is available from the authors on request.

Table 1 Preferred set of underlying concepts for inequality estimates in WIID2

A. **The income concept**	B. **Consumption aggregate**
Canberra Group recommendations for international comparisons of income distribution:	Deaton and Zaidi (2002) recommendations for welfare measurements:
1. Employee income	**1. Food consumption**
Cash wages and salaries	Food purchased from market
2. Income from self-employment	Home produced
Profit/loss from unincorporated enterprise	Received as gift or in kind payment
Imputed income from self-employment	**2. Non-food consumption**
Imputed income from self-employment	Daily use items
Goods and services produced for barter, less cost of inputs	Clothing and house wares
Goods produce for home consumption, less cost of inputs	Health expenses
3. Income less expenses from rentals, except rent of land	Education expenses
4. Property Income	Transport
Interest received less interest paid	*To be excluded*
Dividends	Taxes paid, purchase of assets, repayments of loans and lumpy expenditures
5. Current transfers received	**3. Durable goods**
Social insurance benefits from employers schemes	The use-value (rental value) of durables
Social insurance benefits in cash from government schemes	**4. Housing**
Universal social assistance benefits in cash from government	Rents paid
Mean-tested social assistance benefits in cash from government	If dwelling is owned by household or received free of charge, an estimate of the rental equivalent (imputed rent)
Regular inter-household cash transfers received	
6. Total income (sum of 1 to 5)	Utilities (water, electricity, garbage collection etc.)
7. Current transfers paid	If durables are included with their purchase value or/and taxes paid, purchase of assets, repayments of loans and lumpy expenditures, the concept to be referred to is expenditures
Employees social contributions	
Taxes on income	
8. Disposable income (6 less 7)	

Other conceptual issues

1. Household should be the basic statistical unit
2. Per capita incomes or consumption/expenditure should be measured (The Canberra group recommends the use of equivalence scales but for comparability reasons per capita is chosen)
3. Person weights should be applied

4 Trends in income inequality within countries

While much interest has centered on how the world income distribution is changing, we focus here on the narrower question of how inequality has changed within countries. It is well known that an increase in within-group inequality is neither a necessary nor a sufficient condition for condition for overall inequality to increase. It does seem reasonable, however, to assume that similarities in within-country trends are informative of what is happening to overall inequality.

We begin by looking at graphs of Gini coefficients in the WIID2. We then move on to representing the data at hand in a more parsimonious fashion in order to be able to examine if there are in fact similarities in trends across countries. We finally take a brief look at quintile group shares of income across countries along similar lines to inform us of further patterns in the data.

We show in Figures 1-7 the Gini coefficients of income in the countries in the WIID2 database, organized by region. Several observations are immediately clear from studying these pictures. First, information on within-country trends in inequality is very patchy. For many countries, there is very little information - so little, in fact, that no meaningful statements about within-country trends can be made. This is particularly true for Sub-Saharan Africa, despite the fact that we do not limit our examination to income only. Second, as emphasized by, among others, Atkinson and Brandolini (2001), it is very important to examine changes across time using identical, or highly similar, measures of inequality. Within-country measurements can and do differ in magnitude, and in many cases the timing and even the direction of change depends on the measure used.

Data from Israel demonstrate this quite clearly (see Figure 6). The series using taxable income from the Ministry of Finance (the solid line with circles) suggests inequality *increased* sharply from 1976 to 1987, while the series from the Luxembourg Income Study (dashed line with diamonds) suggests inequality actually *decreased* during that time period and increased more modestly in the mid 1990s. Neither of these series need be wrong, they just measure different things. The Ministry of Finance series measures the inequality of taxable income among tax payers whereas the LIS data measure the inequality of disposable income among the population.

However, even if it is important to emphasize the pitfalls in using secondary data, there are several instances where different sources tell a similar story about inequality. For example, several partially overlapping series from France (see Figure 1) suggest inequality declined there until the

Figure 1 Trends in income inequality – Gini coefficients in OECD

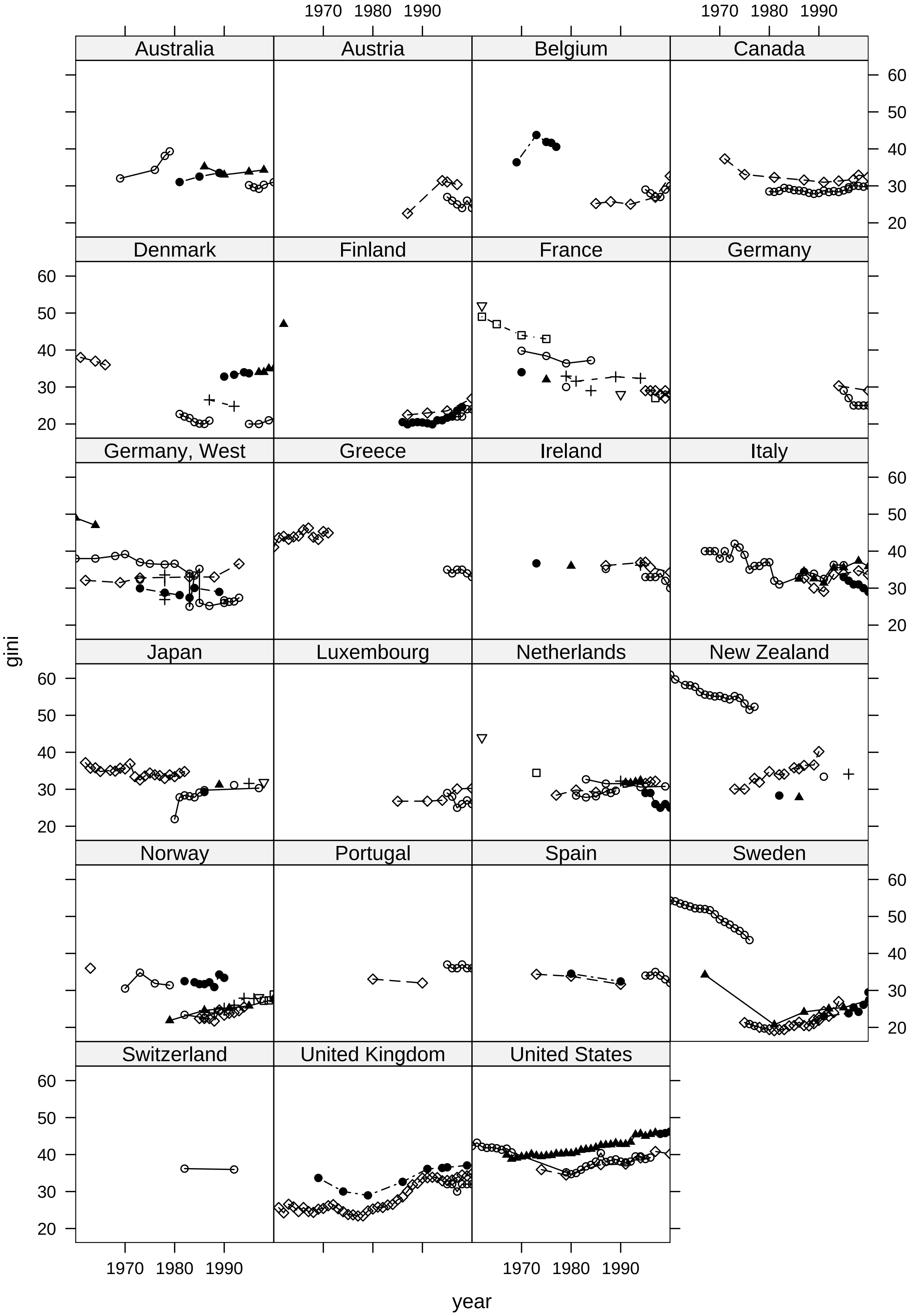


Figure 2 Trends in income inequality – Gini coefficients in Transition countries

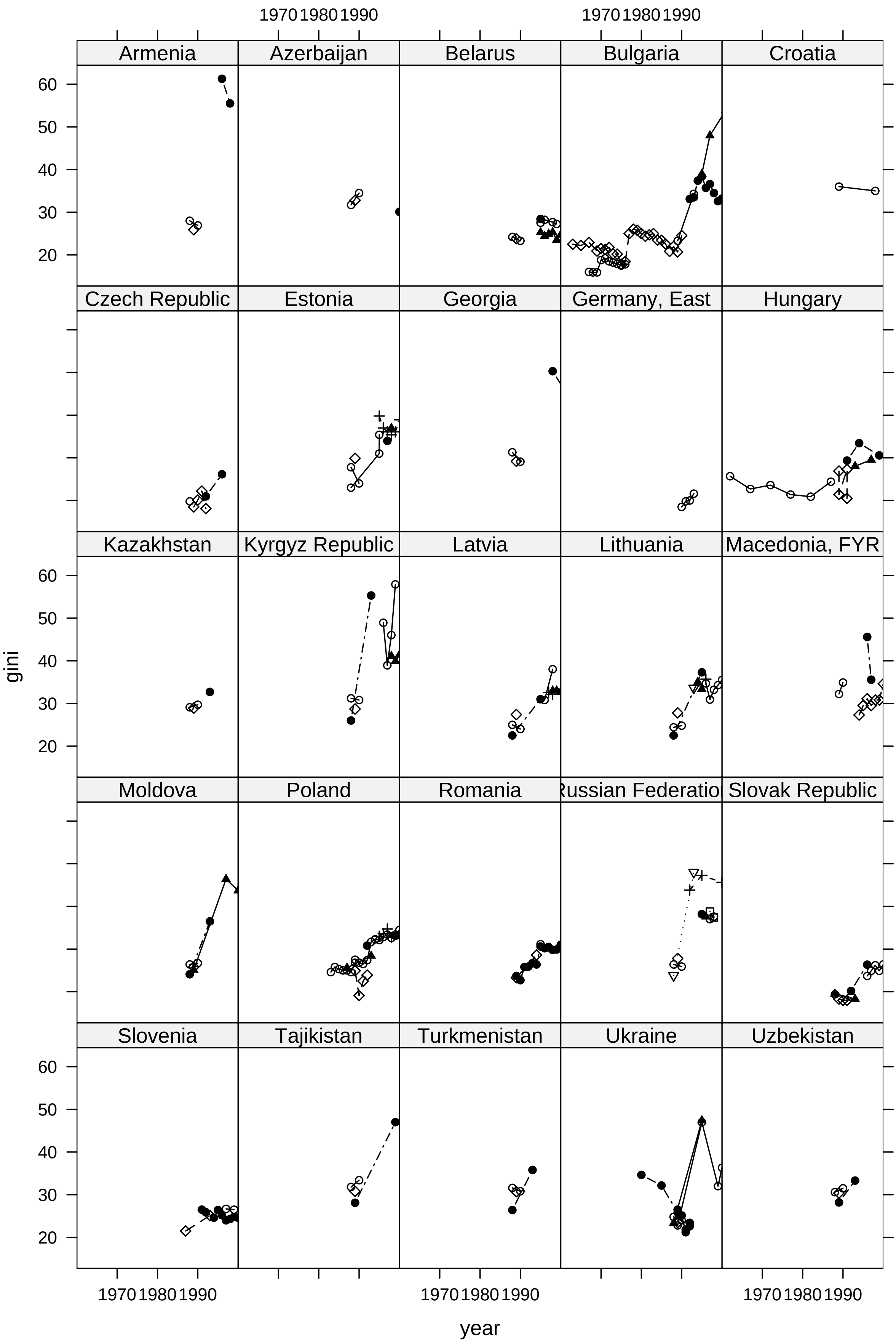


Figure 3 Trends in income inequality – Gini coefficients in Subsaharan Africa

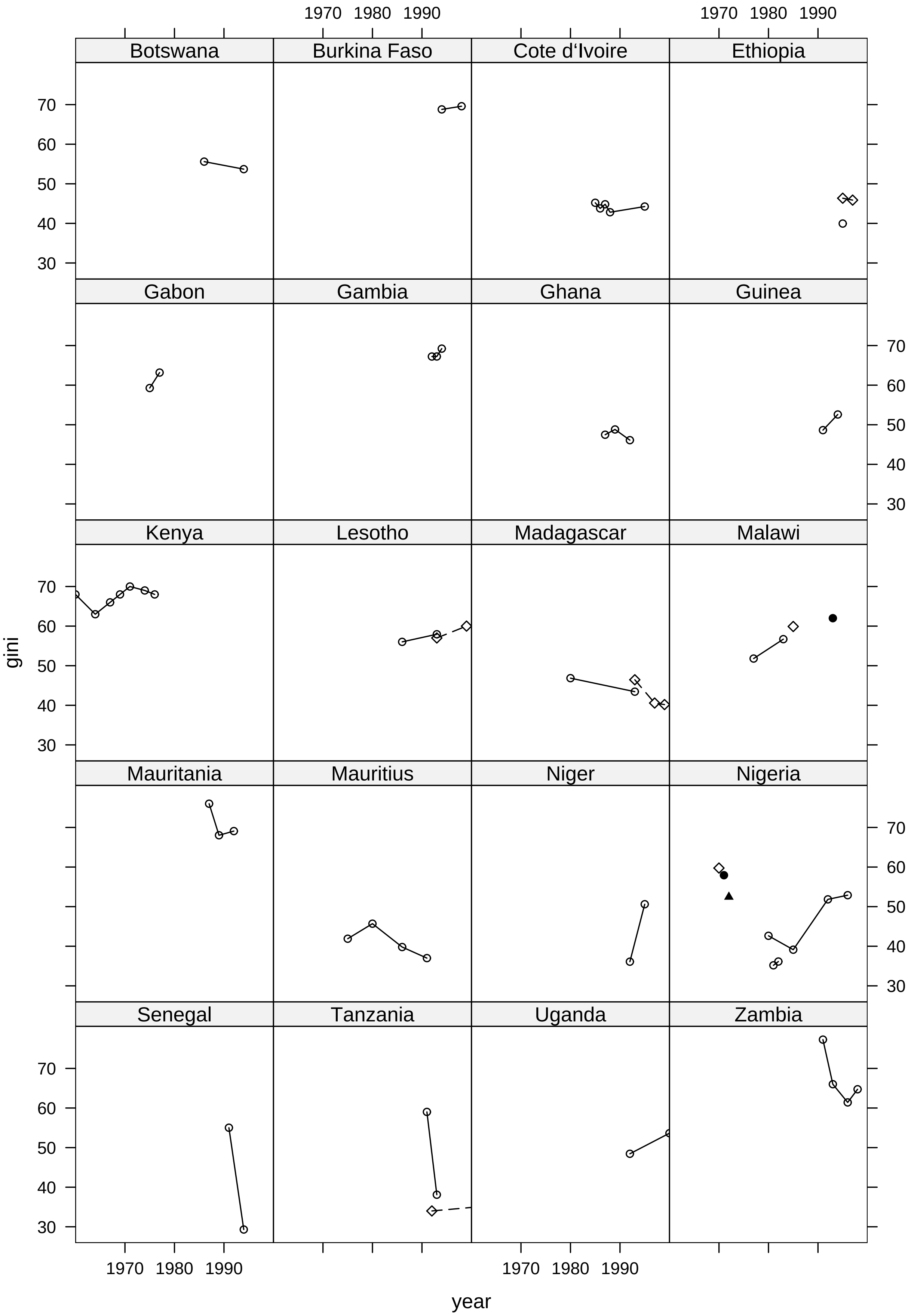


Figure 4 Trends in income inequality – Gini coefficients in Latin America

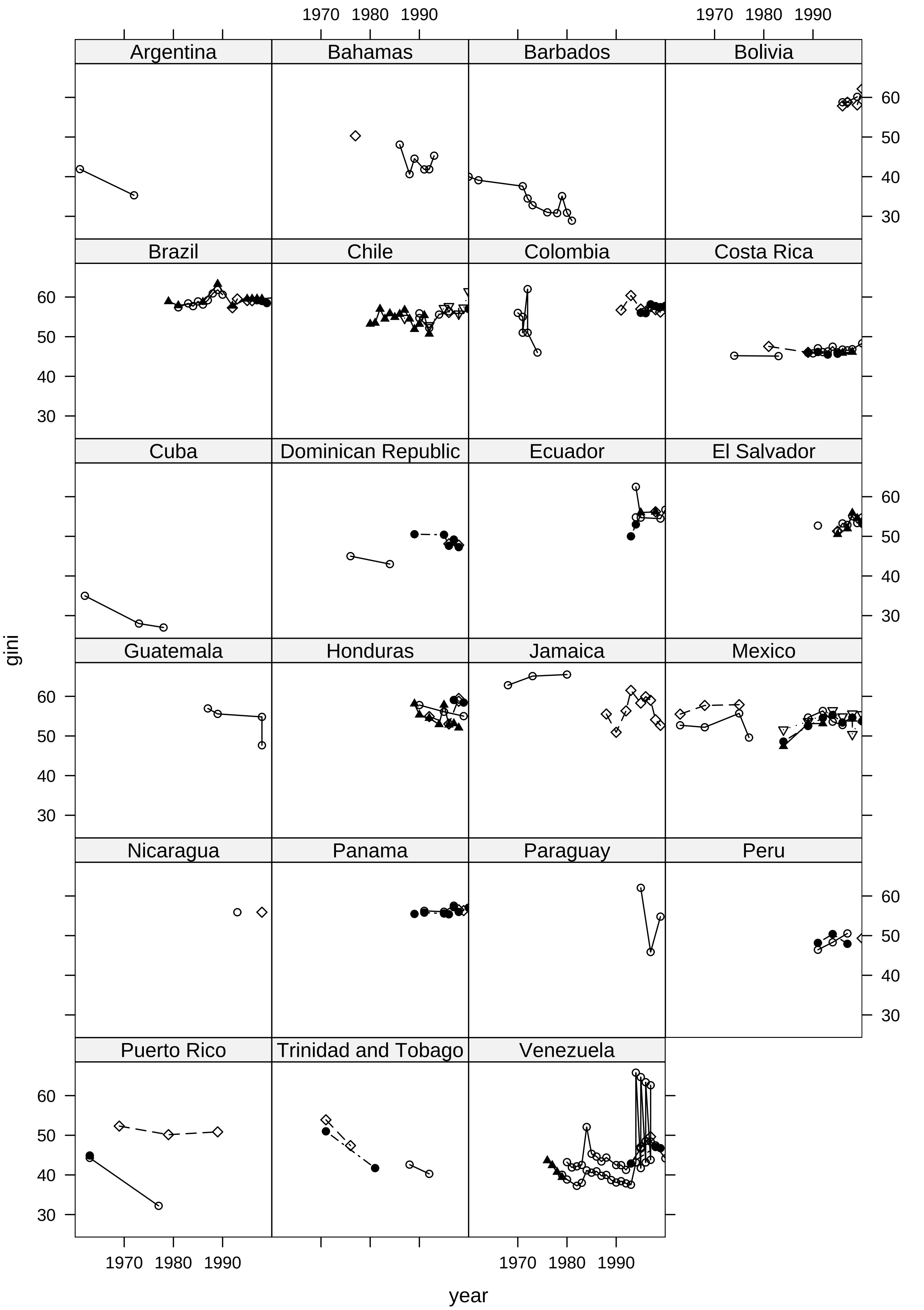


Figure 5 Trends in income inequality – Gini coefficients in SE Asia

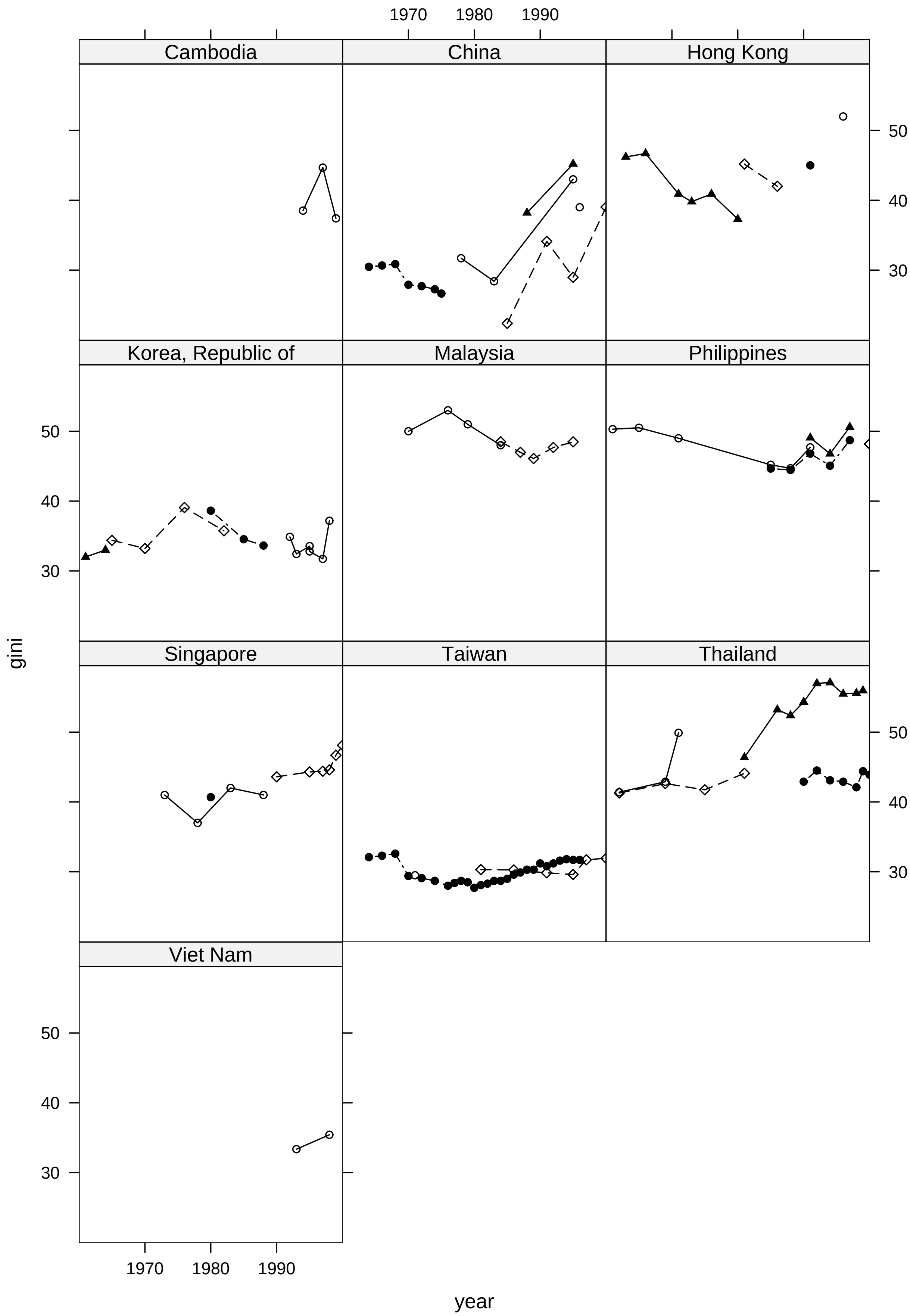


Figure 6 Trends in income inequality – Gini coefficients in Middle East

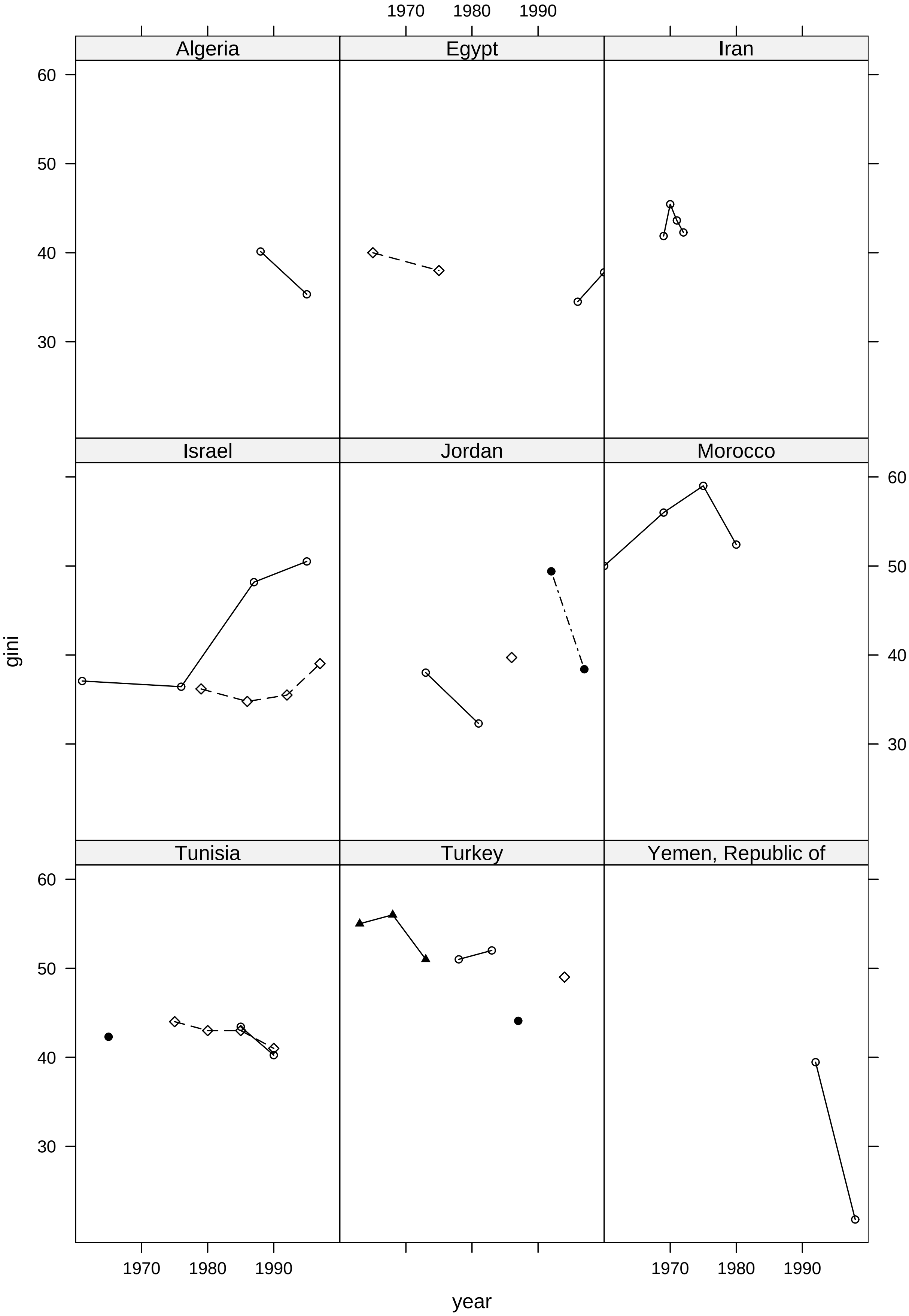
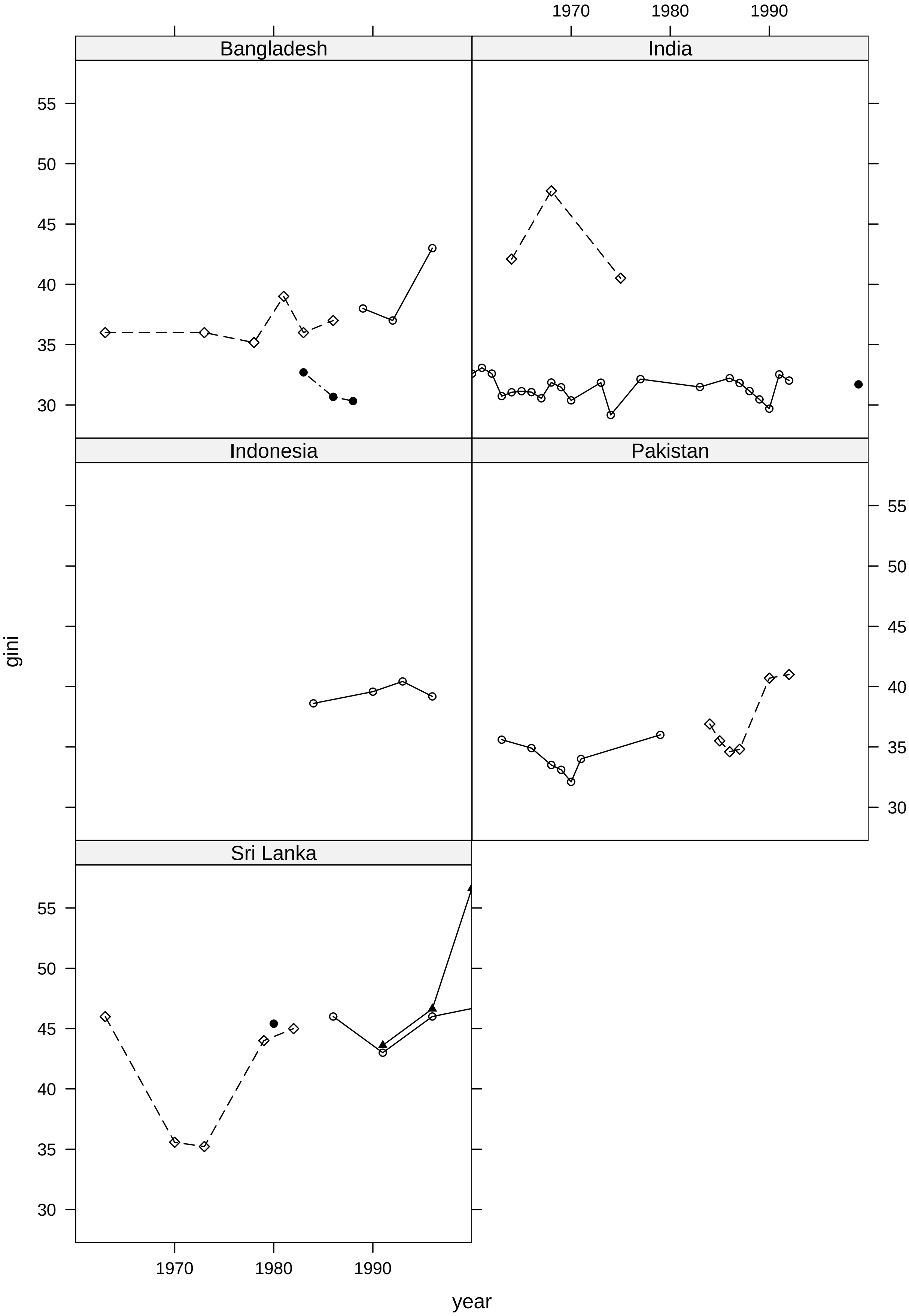


Figure 7 Trends in income inequality – Gini coefficients in South Asia



early 1980s and has since moved little.

This paper is motivated by the debate on trends in inequality. In order to proceed, we need to reduce the dimensionality of the data. To concisely describe our data, we formulate a *linear mixed effects* (lme) model that captures both a (potential) "global" change in inequality and within-country trends, as well as allowing for variations in levels and trends in inequality across different series for the same countries. Specifically, we estimate equations of the form

$$y_{ijt} = \beta_0 + \beta_1 t + \beta_2 t^2/10 + b_{0i} + b_{1i} t + b_{2i} t^2/10 + b_{0ij} + b_{1ij} t + b_{2ij} t^2/10 + \varepsilon_{ijt}, \tag{1}$$

where y_{ijt} is the value of the an inequality index in country i in series j in year t. t is year since 1960 and ε is a "well-behaved" error term. The random coefficients b_{ki} capture variations in the level and trend in inequality in the ith country. We have added a further level of variation, captured by the b_{kij}, to the basic model in equation 1, namely by source, to allow for different levels and trends (if the trend components are included) by series. Equation 1 and its variants are estimated using the `lme` function in the **R** add-on package `nlme` (see Pinheiro and Bates, 1999). The use of `lme` allows us to systematically study differences in trends across countries and sources and to statistically test more and less parsimonious specifications against each other.

It should be noted that we ignore a few inconvenient complications. Most important among them is that fact that we do not adjust for heteroscedasticity. There are at least two potential sources of heteroscedasticity here. First, most of the inequality indices we model are based on sample surveys and thus are subject to sampling variation that varies from survey to survey. Controlling for the heteroscedasticity is, in the absence of detailed information about the samples, is very difficult. The second source of potential heteroscedasticity is the fact that some countries may be subject to greater inherent variability in its inequality series. A comparison of Sweden and Finland, for instance, shows that income inequality as measured by the Gini coefficient of disposable income varies more from year to year in Sweden than in Finland (see Aaberge et al., 2000). The source of this greater variability in Sweden seems to be the greater variability of the inequality of Swedish capital income, which may be driven by the interaction of tax rules and returns on financial assets. For our purposes, the reason for differences in the variation of inequality indices across time are not important. Rather, the heterogeneity introduces nuisance parameters to be dealt with. In this version

Table 2 Estimation results – linear mixed effects models for Gini coefficients

Gini	1	2	3	4	5	6
(Intercept)	46.159 (1.186)	43.006 (1.163)	44.373 (1.913)	42.071 (2.259)	41.170 (1.512)	43.181 (1.395)
year0	−0.321 (0.024)	−0.442 (0.041)	−0.491 (0.064)	−0.317 (0.080)	−0.229 (0.074)	−0.385 (0.075)
year > 1989TRUE	−15.991 (2.098)	NA	NA	NA	NA	NA
year0:year > 1989TRUE	0.635 (0.062)	NA	NA	NA	NA	NA
year0^2	NA	0.011 (0.001)	NA	NA	NA	NA
year0^2/10	NA	NA	0.113 (0.010)	0.082 (0.011)	0.063 (0.017)	0.092 (0.018)
n	1580	1580	1580	1580	1580	1580
σ	5.16	3.09	2.79	2.49	2.47	2.35
logLik	-5.06e+03	-4.57e+03	-4.49e+03	-4.41e+03	-4.4e+03	-4.37e+03
AIC	1.01e+04	9.15e+03	8.99e+03	8.85e+03	8.82e+03	8.78e+03

of the paper, we do not deal with heterogeneity and therefore our conclusions need to be treated with caution.

Table 2 shows the estimated "global" time trends for Gini coefficients, based on the data shown in Figures 8-14. We have experimented with a number of specifications. The first column shows the results of including a linear time trend ("year0", year with 0 in 1960) which is then allowed to change in 1990. The estimated coefficients suggest that "global" inequality – i.e., the average of within-country inequality – decreased up until the late 1980s and started to increase thereafter. In the remaining columns, we have specified a quadratic trend in time, to allow for both the timing of the change to vary across countries and to allow for within-country trends to be flat, follow a U-shaped pattern or an inverted U-shaped pattern. In column 2, we include a random intercept for each country and within each country for each series. In column 3, we allow in addition for a random within-country trend, while column 4 adds a random trend for source within country. In 5 and 6, we have added quadratic terms to the random trends, first only within country and finally also for source. Thus, column 6 shows the "fixed-effect" part of the linear mixed effects model that has a quadratic trend both in the fixed part and in both levels of the random coefficient part. This model is preferred on the grounds of having the lowest information criterion (AIC) and also based on a likelihood ratio test.

The more flexible quadratic specification suggests that, on average, within-country inequality reached its minimum in the early 1980s. It may be more interesting to examine the estimated trends within countries. We therefore have plotted in Figures 8-14 the estimated trends for each country in our data. These trends need to be interpreted with caution, since we have boldly made out-of-sample

Table 3 Estimation results – linear mixed effects models for income quintile group shares

Gini	1	2	3	4
(Intercept)	5.811 (0.473)	5.915 (0.301)	5.732 (0.350)	5.732 (0.350)
Quintile2	4.445 (0.669)	4.594 (0.426)	4.489 (0.495)	4.489 (0.495)
Quintile3	8.831 (0.669)	8.764 (0.426)	8.686 (0.495)	8.686 (0.495)
Quintile4	15.419 (0.669)	15.221 (0.426)	15.318 (0.495)	15.318 (0.495)
Quintile5	42.236 (0.669)	41.878 (0.425)	42.875 (0.495)	42.875 (0.495)
year0	0.004 (0.006)	−0.007 (0.008)	0.002 (0.011)	0.002 (0.011)
Quintile2:year0	−0.002 (0.009)	−0.007 (0.012)	−0.003 (0.015)	−0.003 (0.015)
Quintile3:year0	−0.001 (0.009)	0.004 (0.012)	0.008 (0.015)	0.008 (0.015)
Quintile4:year0	−0.001 (0.009)	0.011 (0.012)	0.007 (0.015)	0.007 (0.015)
Quintile5:year0	−0.016 (0.009)	0.026 (0.012)	−0.021 (0.015)	−0.021 (0.015)
n	7907	7907	7907	7907
σ	2.39	1.87	1.83	1.83
logLik	-1.91e+04	-1.94e+04	-1.93e+04	-1.93e+04
AIC	3.82e+04	3.87e+04	3.86e+04	3.86e+04

predictions for all countries, regardless of the support in the data (in terms of the year in which inequality is in fact observed in the country). We have plotted the "top-level" or within-country trends, which abstracts from the variation in trends within a country but across different sources. These "top-level" trends capture an average across different sources and are therefore no more or less correct than the sources on which they are based.

We note that the direction of change is consistent in the OECD countries, where the estimated quadratic trends point to an increase in inequality except for France (see Figure 8) . In many cases, however, the increase in the 1990s is very slight, and the timing of the increases also varies quite a bit. Inequality in Eastern and Central European countries is also quite consistently estimated to have increased, although the scarcity of data here (as in many other cases) suggest some caution is in order (see Figure 9) . Sub-Saharan Africa (Figure 10), where data are very scarce, exhibits increases in some and decreases in other countries, as does Latin America (Figure 11). Of the East Asian countries in Figure 12 only Malaysia shows decreased inequality while both North Africa & the Middle East and South Asia show more varied patterns. Based on these estimated random quadratic trends, it seems reasonable to say that inequality has been on the increase in most of the countries for which we have data.

We show, finally, our estimated fixed effects results for the quintile group shares. We estimated models that allowed for country, source and quintile group intercepts and quadratic trends. These

Figure 8 Income inequality – random trends for Gini coefficients in OECD

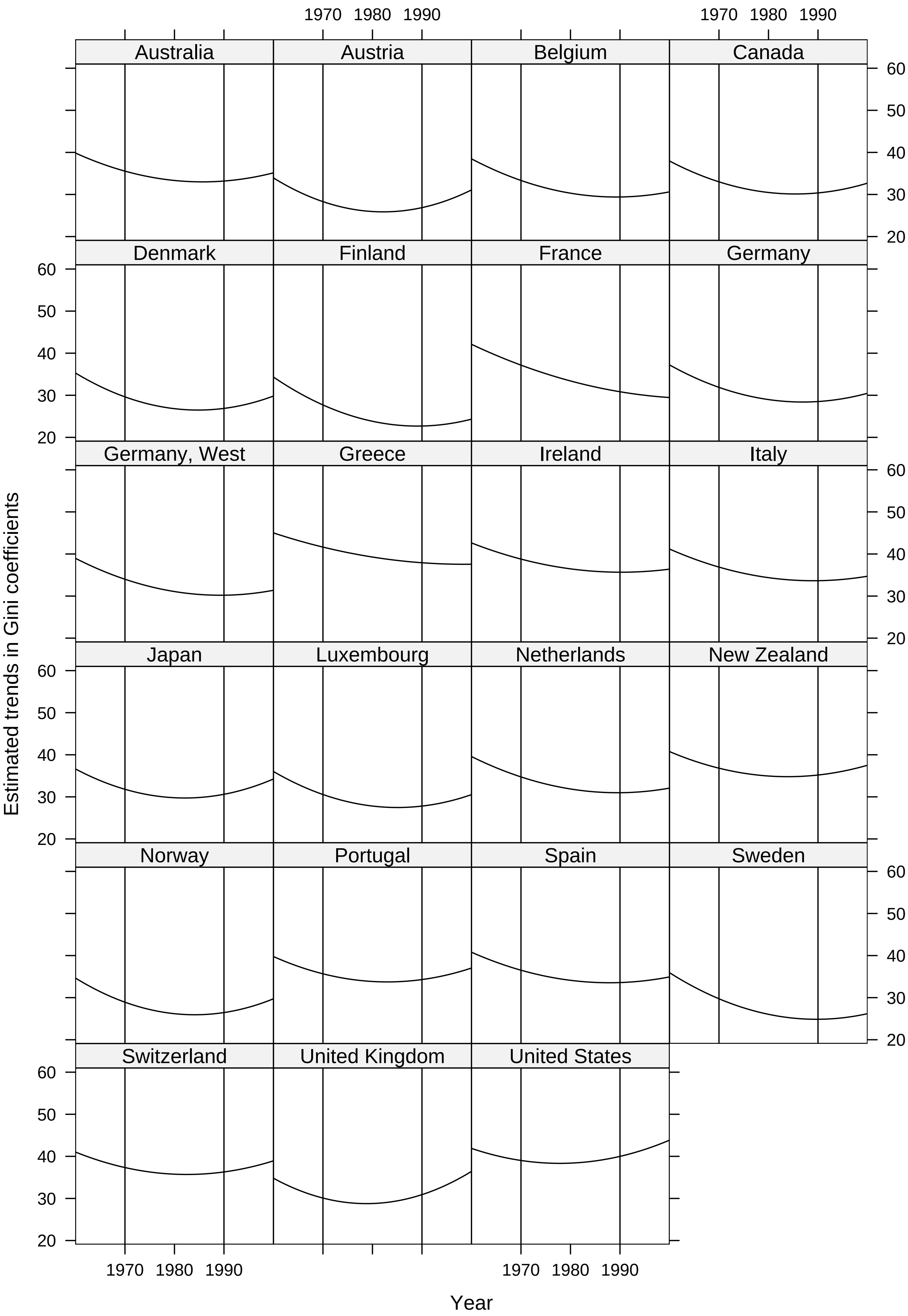


Figure 9 Income inequality – random trends for Gini coefficients in Transition countries

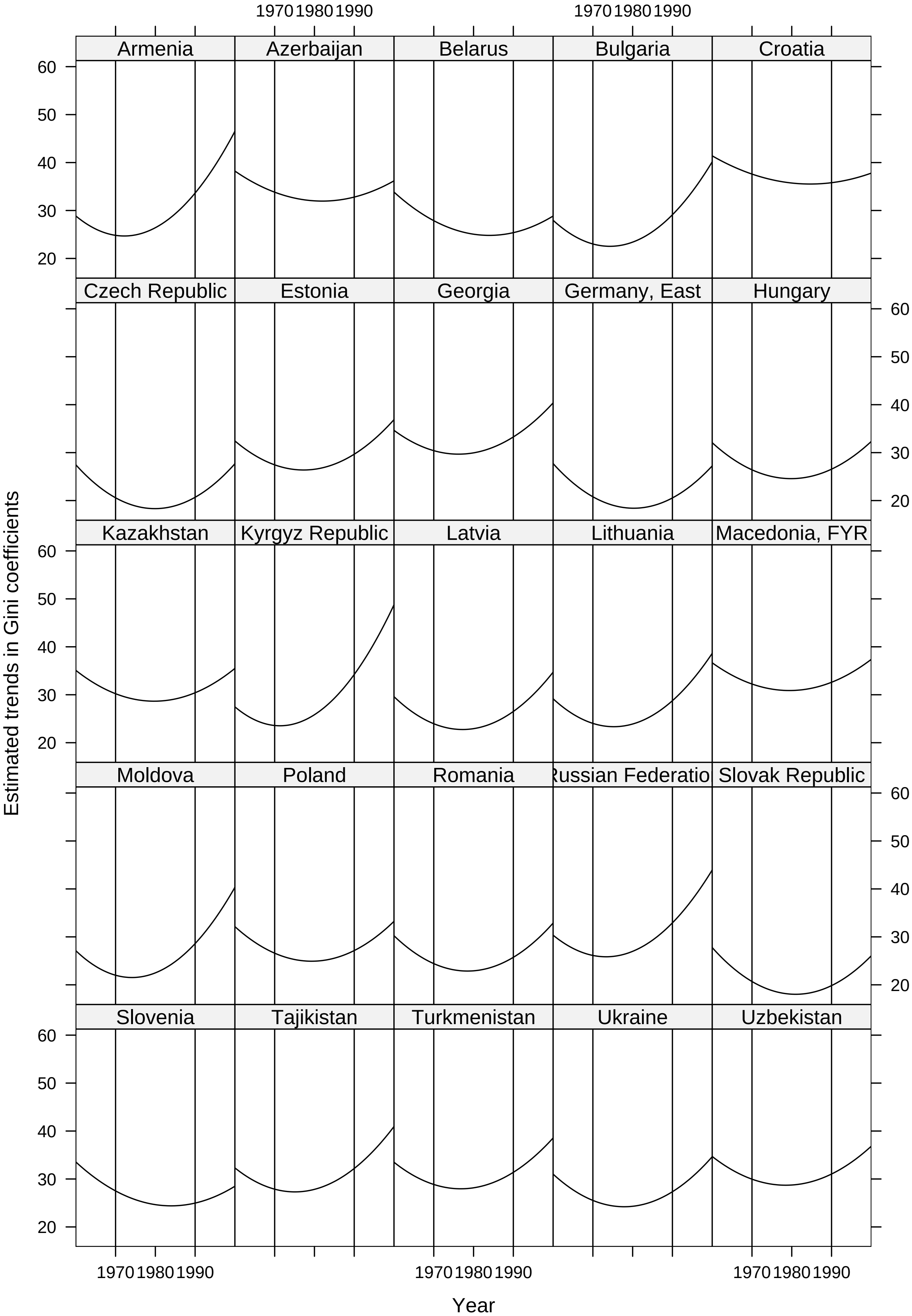


Figure 10 Income inequality – random trends for Gini coefficients in Subsaharan Africa

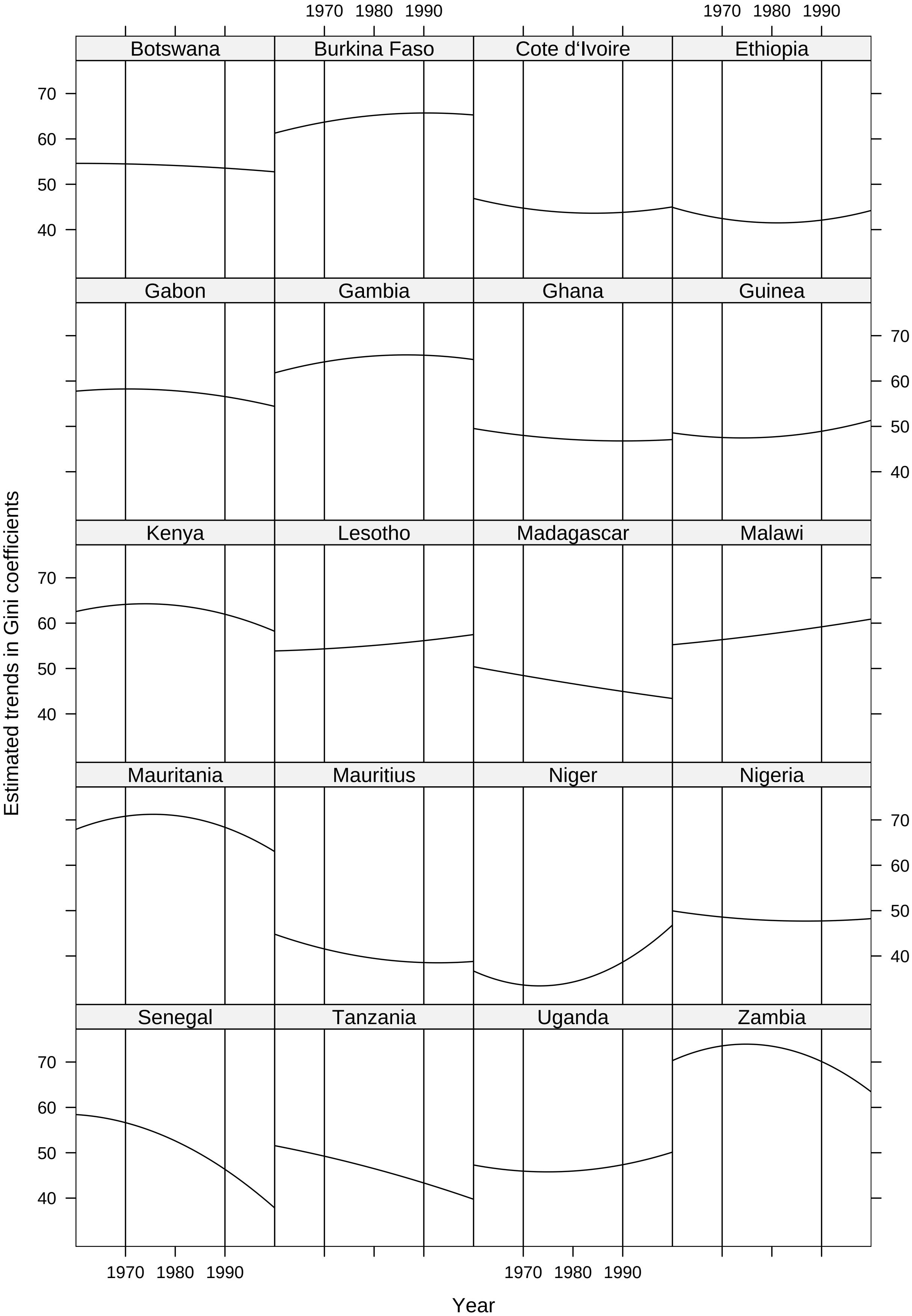


Figure 11 Income inequality – random trends for Gini coefficients in Latin America

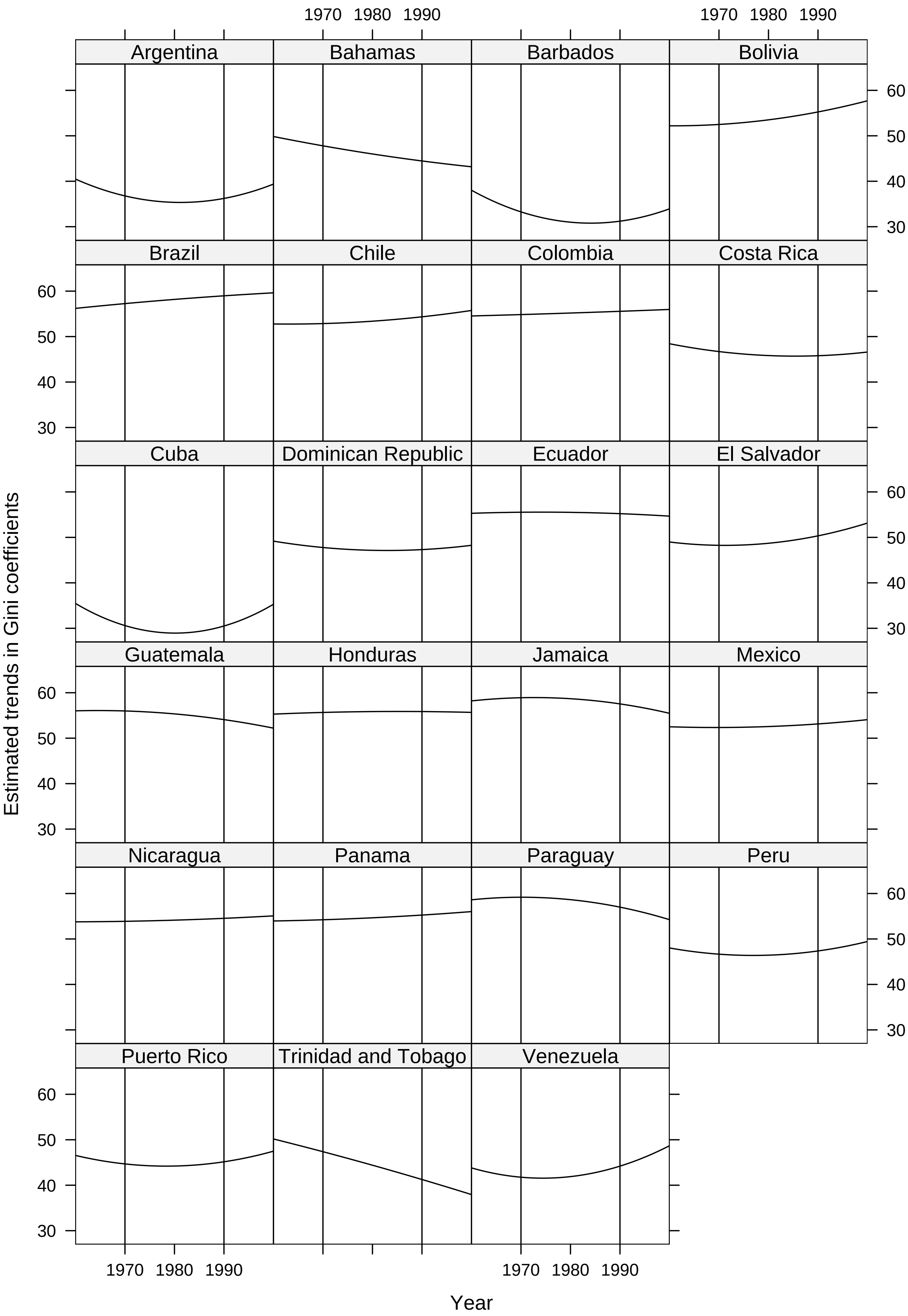


Figure 12 Income inequality – random trends for Gini coefficients in SE Asia

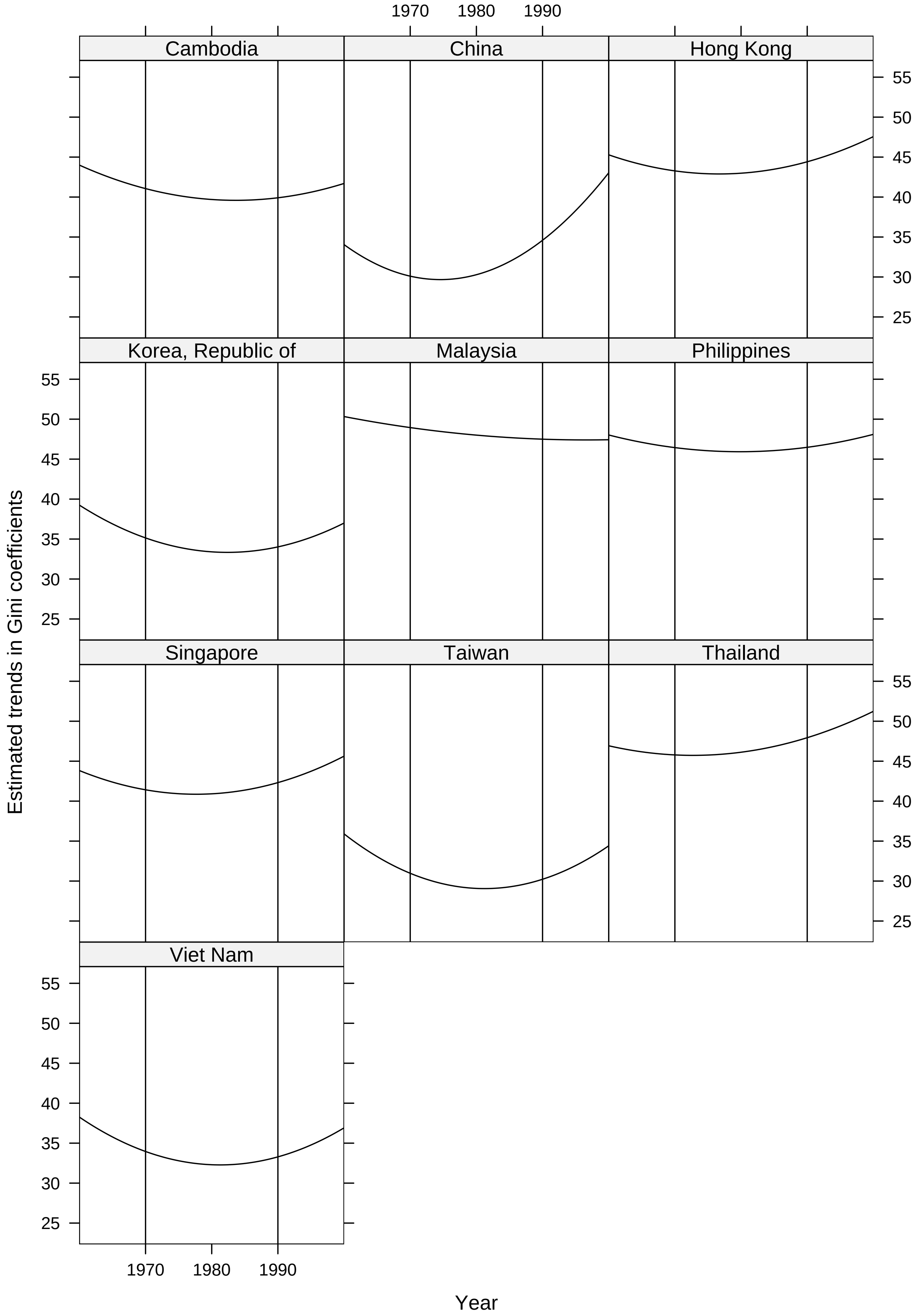


Figure 13 Income inequality – random trends for Gini coefficients in Middle East

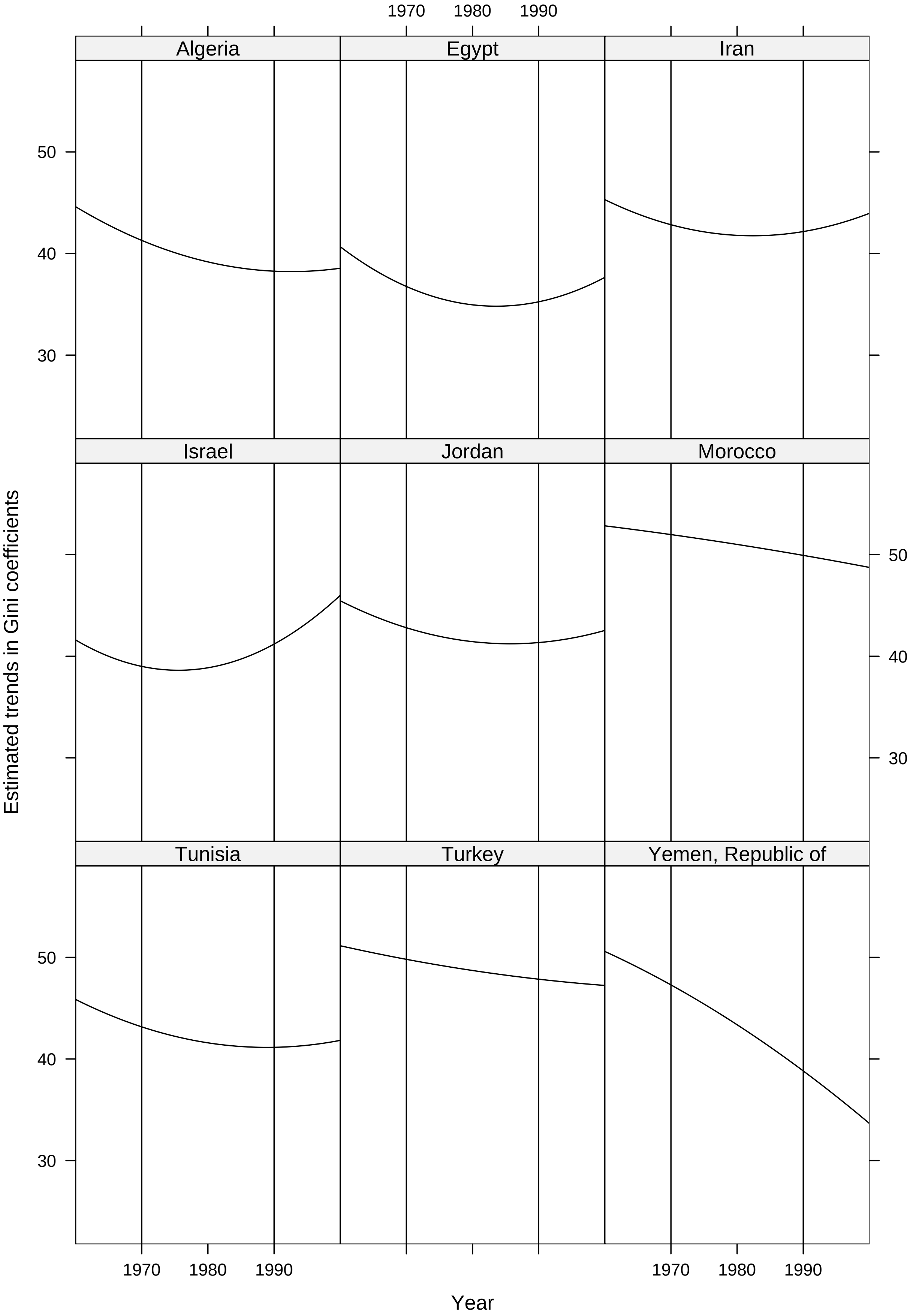
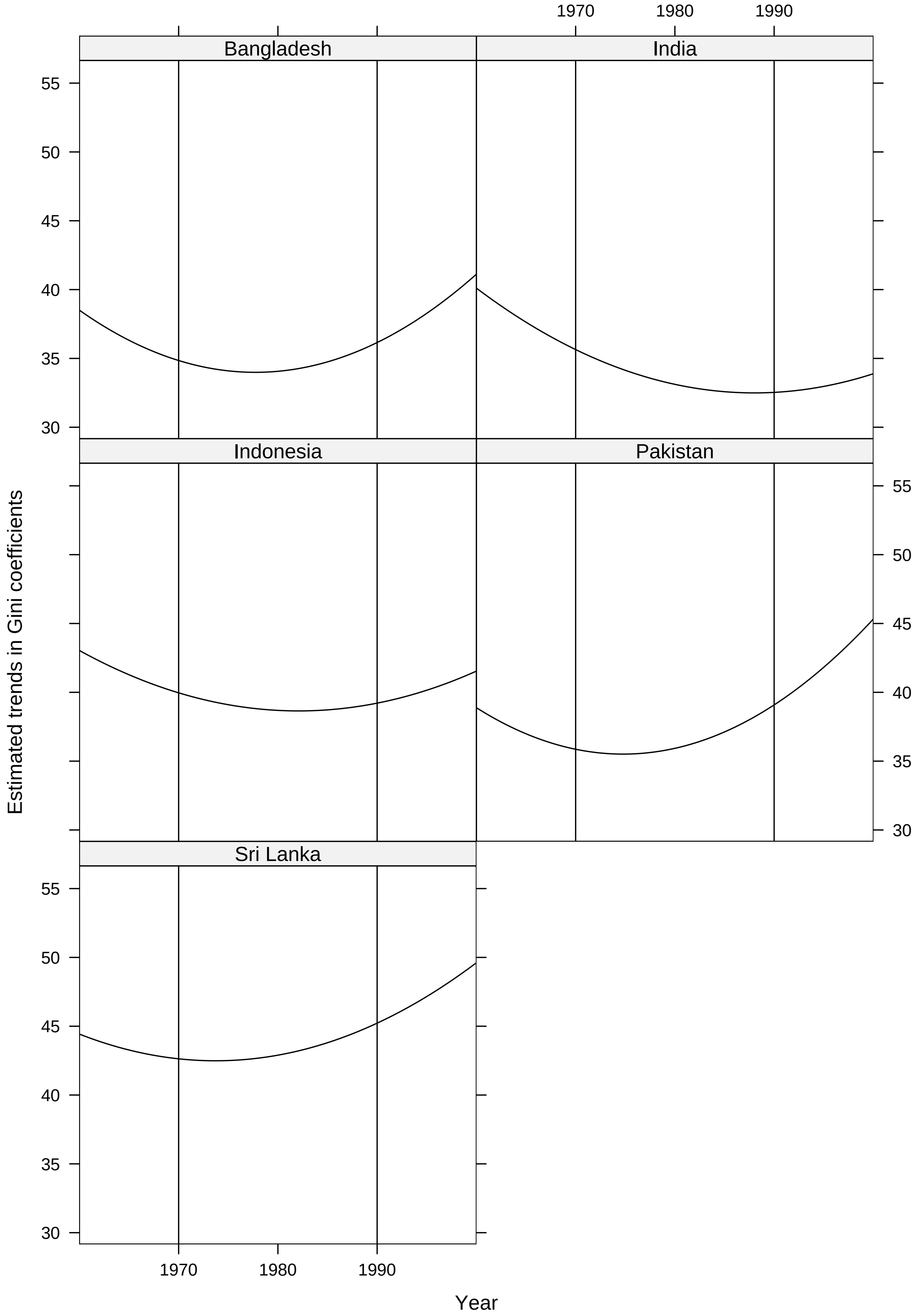


Figure 14 Income inequality – random trends for Gini coefficients in South Asia



were more complex models turned out not to be preferred on statistical grounds to the more parsimonious model which allows only the intercept within each country of the quintile group share to vary, rather than also the time trend. Thus, our preferred model in Table 2 is the first column. On the other hand, the estimated coefficients in the fixed-effects part of the model suggest quite similar patterns of inequality change.

The parametrization here is in interaction form, i.e., we have interacted the time trend with quintile group. The poorest fifth is the reference category. The fixed-effect effect part of the equation includes for each quintile group a quadratic polynomial in time (measures, as above, as years since 1960). The estimated coefficients for the time trends suggest that the shares of four first quintile groups followed an inverted U-shaped pattern across time, while the richest fifth changed in a proper U-shaped pattern. In other words, the increase, on average, of inequality across countries as measured by the quadratic polynomial of the Gini coefficient was driven by decreases across four fifths of the "population" and increases among the top income group.

5 Concluding comments

This paper has used a new compilation of inequality estimates from as many countries in the World is available. Our purpose has been to try to characterize in a critical manner, but using as much information as is possible, the trends within-country inequality. The need to robustly characterize such trends is evident from the controversial and opposite conclusions of world income inequality found by Milanovic (2002*b*) and Sala-i-Martin (2002*a*).

While our intent has been modest – we have focused on within-country changes rather than changes in world inequality – our results certainly suggest that in most countries, based on the available evidence, inequality has tended to increase. Moreover, the increase seems to have occurred mainly through a disproportionate increase in the income share of the richest fifth.

We note, in closing, that our findings can be extended in two quite different directions. First, given both similarities and differences in the trends in inequality across countries, there seems ample scope to extend our regression-based approach to include as regressors the explanatory variables that are likely to account for the changes across time in inequality. Second, our approach could be developed to allow for more robust conclusions of the effects of income inequality on different socio-economic phenomena, including the effect of inequality on growth. In particular, our regression-based approach can be developed to provide first-stage regressions that can mitigate the problems associated with non-standard measurement errors in inequality indices that will cause difficult problems for estimating the effects of inequality on growth.

Figure 15 Trends in income inequality – quintile group income shares in OECD

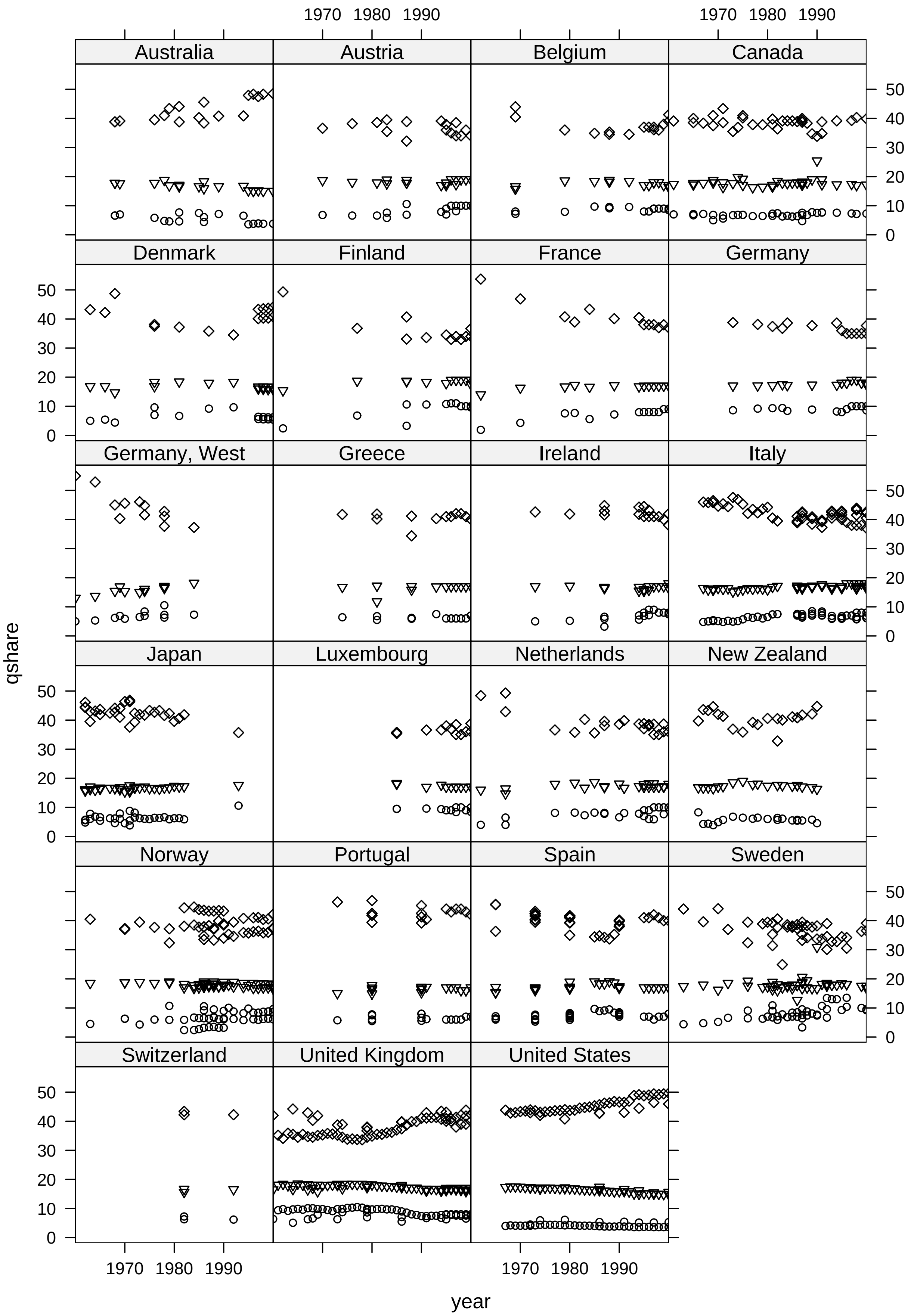


Figure 16 Trends in income inequality – quintile group income shares in Transition countries

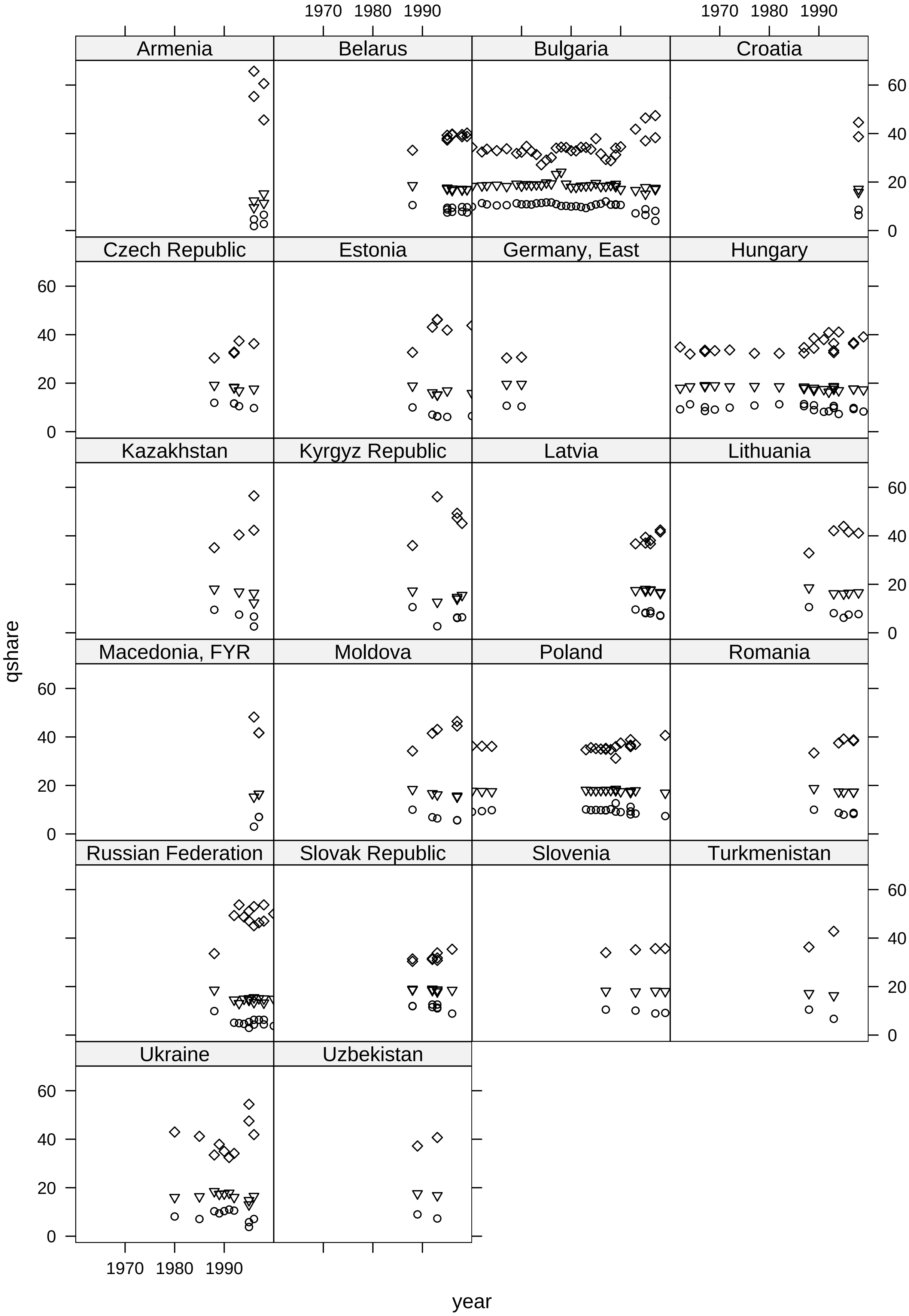


Figure 17 Trends in income inequality – quintile group income shares in Subsaharan Africa

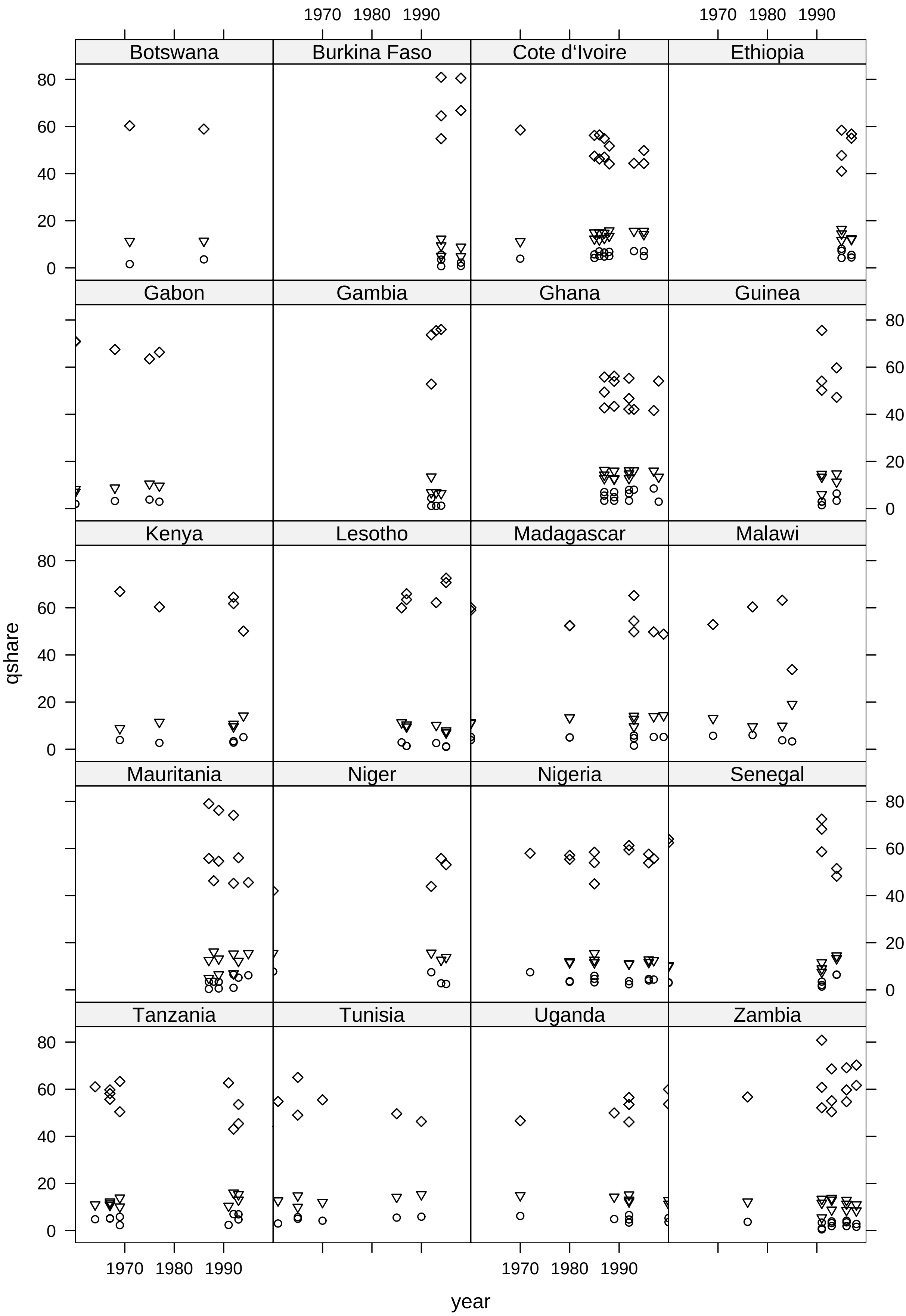


Figure 18 Trends in income inequality – quintile group income shares in Latin America

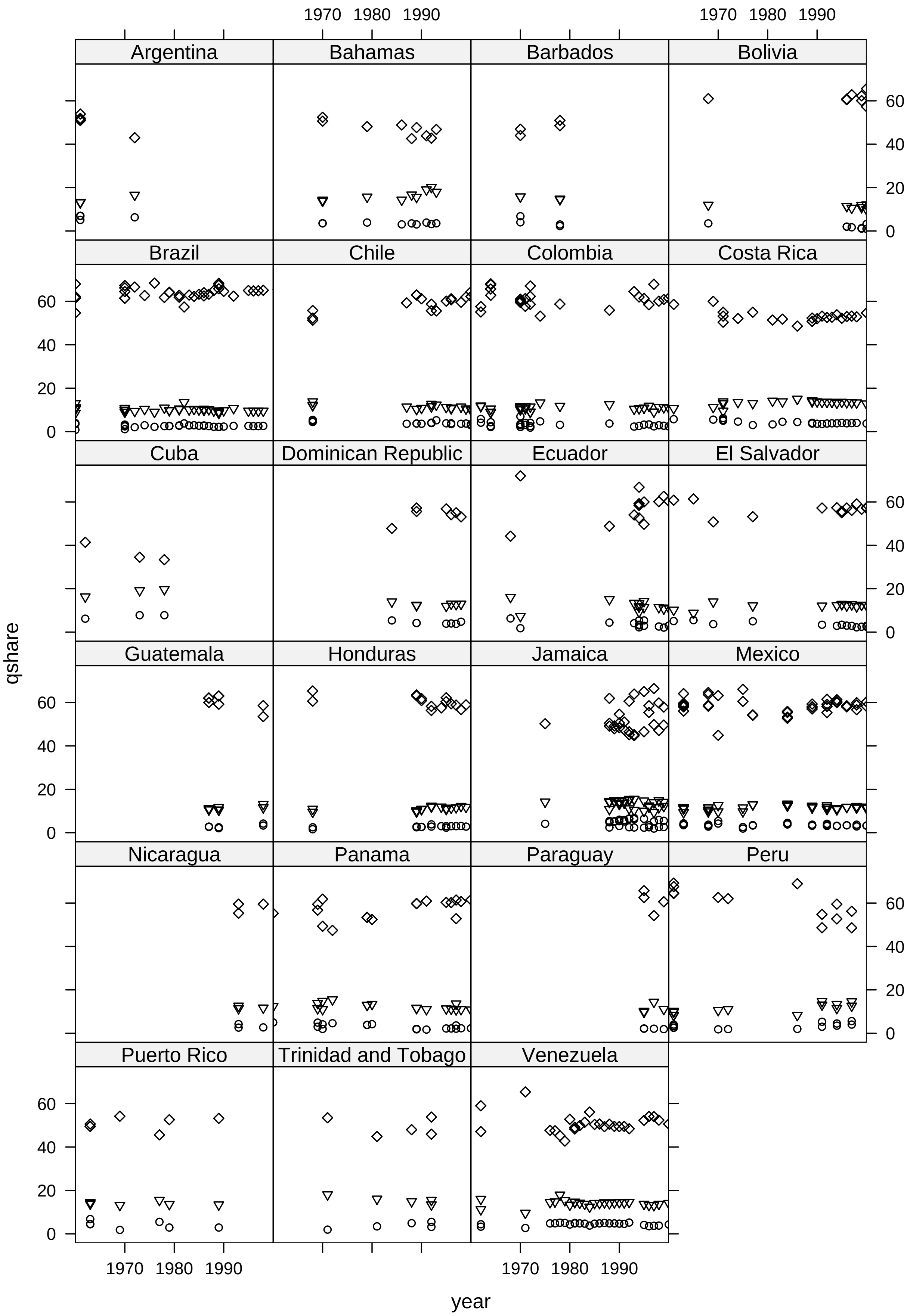


Figure 19 Trends in income inequality – quintile group income shares in SE Asia

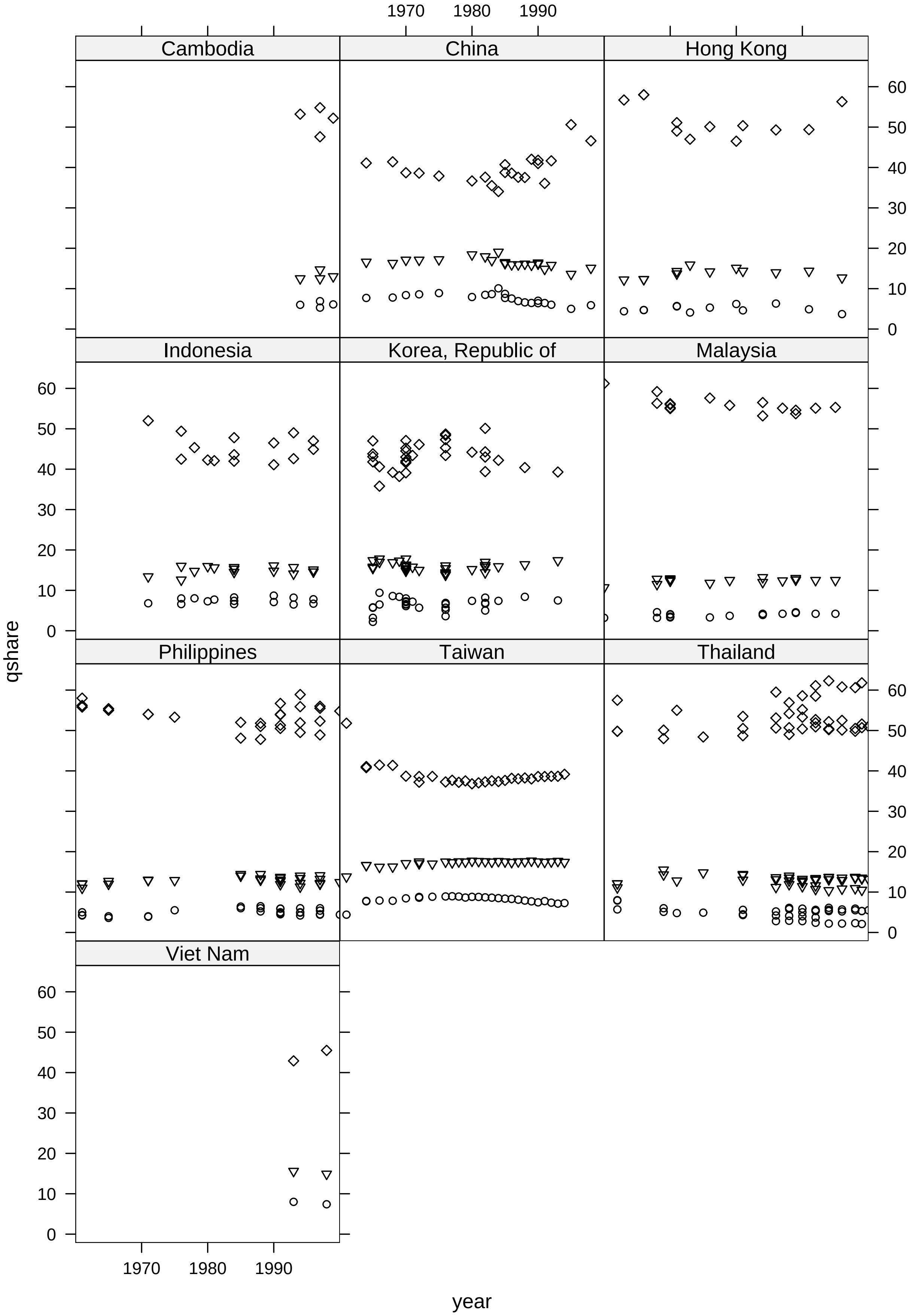


Figure 20 Trends in income inequality – quintile group income shares in Middle East

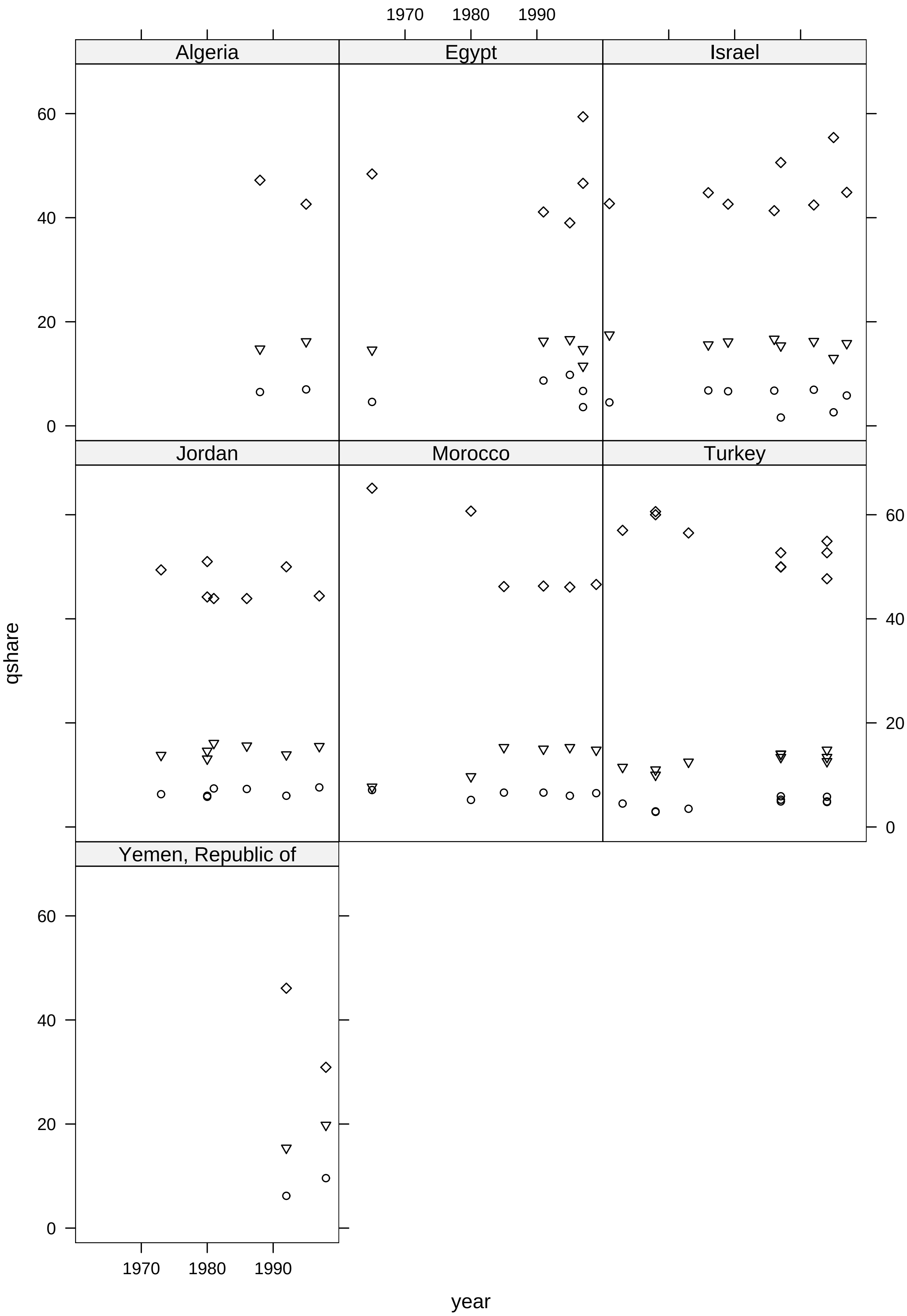
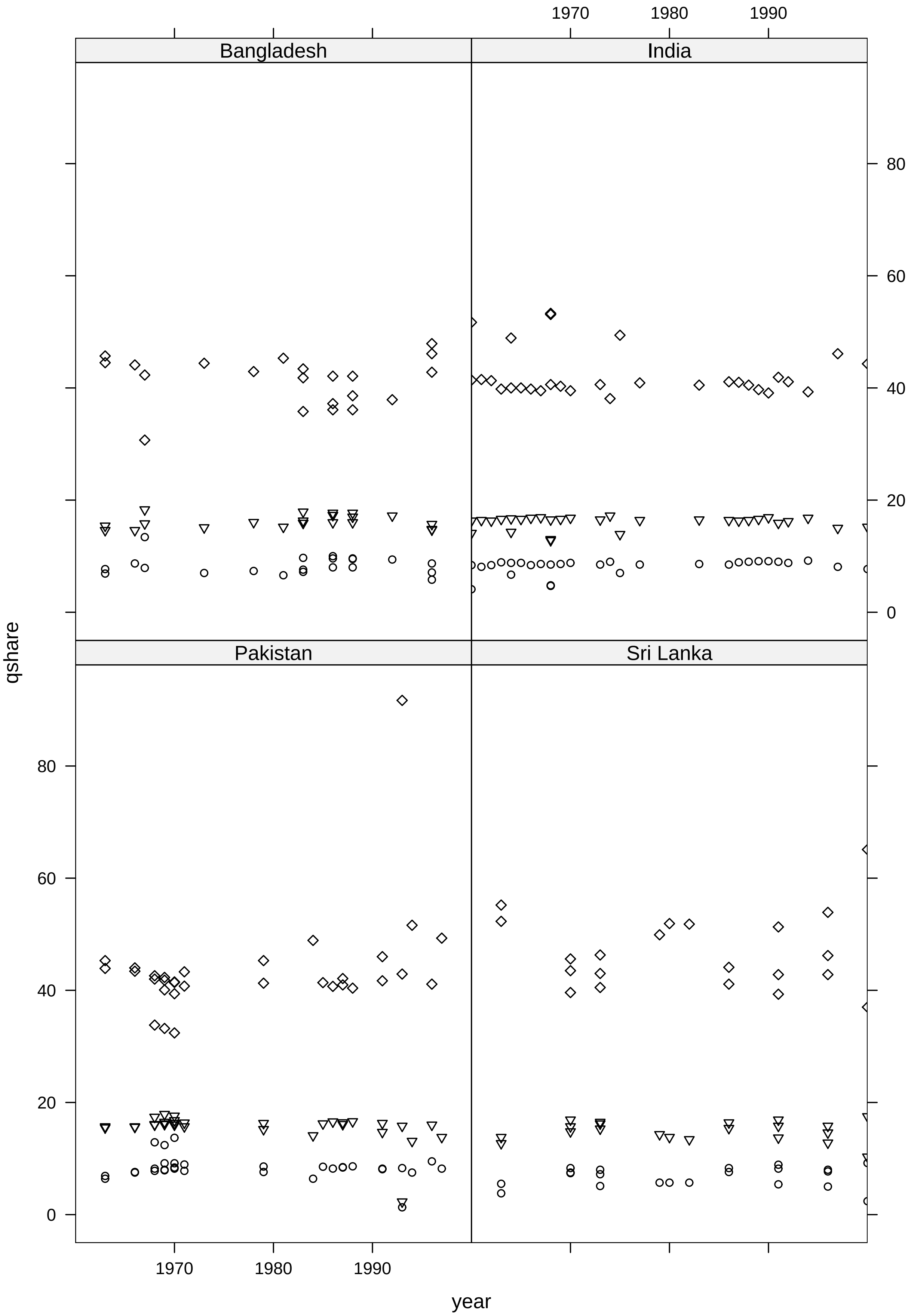


Figure 21 Trends in income inequality – quintile group income shares in South Asia



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