Intertemporal Choice and Inequality in Low-Income Countries: Evidence from Thailand, Pakistan, and India*

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Abstract

It is well known that within-cohort consumption inequality increases with age in developed countries. This pattern is consistent with the permanent income hypothesis, according to which households smooth consumption through credit markets in the short run against transient shocks and in the longer run over the life cycle. This paper provides evidence regarding the age effects in within-cohort inequality for several low-income developing countries, where credit markets are underdeveloped. We find patterns previously unnoticed in the literature. Within-cohort inequality in consumption often decreases with age, and the divergence of the pattern from those observed in developed countries is larger among uneducated and rural households. We provide an interpretation that the decreasing age effect in consumption inequality within cohort, found widely in low-income regions and classes in Asia, is consistent with partial insurance models, either with within-cohort inequality in income decreasing with age, or with insurance efficiency increasing with age.

1 Introduction

It is well known that within-cohort consumption inequality increases with age in developed countries. This pattern is consistent with the permanent income hypothesis, according to which households smooth consumption in the short run against transient shocks and in the longer run over the life cycle. Deaton and Paxson (1994) establishes that inequality does indeed increase with age in the US, Great Britain, and Taiwan, and increases at roughly similar rates. Deaton and Paxson interpret this as the reflection of cumulative differences in the effects of luck on consumption. Storesletten et al. (2004) extend this analysis for the US case, showing that age effects in income and consumption inequality within cohort are indeed consistent with the theoretical predictions of an overlapping-generations general equilibrium model in which households face uninsurable earnings shocks over the course of

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their lifetime. More recently, there have been a number of empirical studies that attempt to link changes in consumption inequality in high-income countries with models of partial insurance (e.g., Blundell et al., 2008; Krueger and Perri, 2006), but we are unaware of any similar efforts for low-income countries.

People in low-income developing countries and particularly poorer and less-educated farmers in low-income countries may have limited ability to hedge against the vagaries of income shocks that may put their livelihood at risk (Fafchamps, 2003; Dercon, 2005). This implies that the income shocks realized throughout their working years may have a larger impact on the consumption dynamics of households in these countries than is observed for wealthier, better-educated households in high-income countries.

On the other hand, the development of credit markets in low-income countries has lagged behind the development of output and other factor markets (Kochar, 1997a; 1997b). As a consequence, poor households in these countries may have difficulty in smoothing consumption intertemporally through credit markets.

The increasing within-cohort consumption inequality documented by Deaton and Paxson makes sense, in light of the relatively well-developed credit markets available to households in high-income countries. The well-documented shortcomings of credit markets in many lower-income countries leads us to ask whether the same pattern of increasing within-cohort inequality also prevails in these environments.

The shape of the age effect in inequality will give us important information regarding the intertemporal choice available to residents in low-income countries. In spite of this importance, there are very few studies that directly extended the empirical exercises of Deaton and Paxson to these countries. Although there are many empirical studies on changes in consumption inequality in developing countries (see e.g., World Bank, 2006; Shorrocks and van der Hoeven, 2004, and references therein) most of these do not explicitly link their empirical findings with theoretical models of intertemporal choice. Jeong and Townsend (2008), Townsend and Ueda (2006), Gine and Townsend (2004) are notable exceptions, though their focus is on intertemporal occupational choice in an environment distorted by credit market failures. In this paper, we follow Deaton and Paxson (1994) in focusing on the intertemporal choice households make of how much to consume out of income in the face of risk and incomplete markets.

Given this paucity in the literature, this paper attempts to accumulate evidence regarding the age effects in within-cohort inequality for several developing countries, in the spirit of Deaton and Paxson (1994). To investigate the intertemporal choice available to consumers, the ideal datasets should include long-period panel data of income and consumption for a large number of sample households (see Blundell et al., 2008, for the US case).

However, such datasets are not readily available for developing countries. For this reason, we start with the framework by Deaton and Paxson, which only requires repeated cross-section datasets of household consumption expenditures covering as many years as possible. We employ datasets satisfying this requirement from Thailand, Pakistan, and India. To increase statistical efficiency as well as to control for changes in household demographics, we extend the cohort-level regression model by Deaton and Paxson to a model at the household level. In sharp contrast to the pattern observed by Deaton and Paxson in high income countries, we find that in these low income countries within-cohort inequality in consumption often decreases with age. Further, the divergence of the pattern from those observed in developed countries is larger among uneducated and rural households.

The remainder of the paper is organized as follows. The next section explains an empirical model to estimate the age effect in within-cohort inequality. The datasets are described in Section 3, while the empirical results are presented in Section 4. A speculative discussion to associate the findings of this paper with theories of intertemporal choice is given in Section 5.

2 Empirical Specification

Let c_{igt} be the per-capita real consumption expenditure for individual/household i belonging to cohort group g for the survey round t. We define cohort by the birth year of the household head. We treat i as the individual or the household interchangeably in theoretical discussion while we treat i as the household weighted by its number of household members in empirical analyses since all expenditure data are at the household level.

Given cross-section data of c_{igt} for year t, we can calculate various measures of inequality within cohort by aggregating c_{igt} across i belonging to g. Following the literature, we employ the variance of log consumption as the main measure of inequality in this paper, i.e., $\text{Ineq}_{gt} = \text{var}_{i \in g}(\log c_{igt})$.

Deaton and Paxson (1994, Figures 1–3) first plot the observed values of Ineq_{gt} for the same cohort g but in different years t on the axis of the age of the household head. These plots show an increasing age effect for most cohorts in US, Great Britain, and Taiwan. In sharp contrast, Thai data, whose details are described in the next section, do not show such a pattern. Figure 0-1 plots within-cohort inequality for Thailand: the cohort born in 1942-43 (dark red) experienced an increase in inequality while the cohort born 1958-59 experienced a decrease in inequality, with the remaining three cohorts experiencing up and down. Assuming that each cohort is associated with a cohort-specific inequality level, the shape of the within-cohort inequality over the whole life cycle can be identified by the cohort-level regression model of Deaton and Paxson (1994):

$$\text{Ineq}_{gt} = \text{var}_{i\in g}(\log c_{igt}) = \sum_a \alpha_a Age_{gt} + \sum_g \beta_g Cohort_g + u_{gt}, \tag{1}$$

which is basically a regression of the cohort-level inequality on age fixed effects (α_a) and cohort fixed effects (β_g). For each cohort, the cohort fixed effect adjusts the curves plotted in Figure 0-1 in a parallel way, so that the age fixed effects smoothly connect the shapes of younger cohorts, middle cohorts, and older cohorts. Therefore, fitted values of the age fixed effects, $\hat{\alpha}_a$, show the dynamics of within-cohort inequality across age and their confidence intervals can be estimated from the standard errors of $\hat{\alpha}_a$. Figure 4 of Deaton and Paxson (1994) shows the age effects thus compiled, which increase with age at a similar speed in US, Great Britain, and Taiwan. As suggested by Figure 0-1, the Thai data do not show such a pattern, which we will discuss in more detail in Section 4.

In the same spirit as Deaton and Paxson, we estimate a household-level model:

$$(\log c_{igt} - \bar{\log} c_{gt})^2 = \sum_a \alpha_a Age_{igt} + \sum_g \beta_g Cohort_{ig} + X_{igt}\gamma + u_{igt}, \tag{2}$$

where $\bar{\log} c_{gt}$ is the cohort average of $\log c_{igt}$ for $i \in g$ in year t, X_{igt} is a vector of demographic variables that characterize household i in year t and region fixed effects. By adopting this specification, we can expect a gain in statistical efficiency as well as we can control for sampling designs of each survey or for changes in household demographics in a more straightforward way. Similarly to Deaton and Paxson (1994), fitted values of the age fixed effects, $\hat{\alpha}_a$, show the dynamics of within-cohort inequality across age and their confidence intervals can be estimated from standard errors of $\hat{\alpha}_a$.

In estimating either (1) or (2), it should be noted that macroeconomic shocks (which can be represented by survey-round fixed effects) are already controlled in an implicit way through the combination of the cohort fixed effects and the age fixed effects. It is well-known that age, cohort, and year fixed effects are perfectly collinear so that it is not possible to identify all of them in a linear model. When cohorts in different rounds in the repeated cross-section dataset are well-overlapping (i.e., the repeated cross-section dataset with a long time horizon), age effects are estimated reliably, while the parameter estimates for the age effects become unstable in the repeated cross-section dataset with a short time horizon because the identification is based on a smaller number of overlaps of cohorts.

If age effects thus estimated by either (1) or (2) are approximately linear, which is indeed the case for the three countries analyzed by Deaton and Paxson (1994), we can estimate restricted versions of (1) and (2) as

$$\text{Ineq}_{gt} = \alpha \text{Age}_{gt} + \sum_g \beta_g \text{Cohort}_g + u_{gt}, \tag{3}$$

$$(\log c_{igt} - \bar{\log} c_{gt})^2 = \alpha \text{Age}_{igt} + \sum_g \beta_g Cohort_{ig} + X_{igt}\gamma + u_{igt}, \tag{4}$$

where parameter α is the linear rate of increase or decrease in inequality. We can run a simple Wald test of this specification against the more general one with a full set of age fixed effects ((1) or (2)). We can also construct simple tests of hypothesis based on specifications (3) or (4) such as "within-cohort inequality is increasing (decreasing) over time" by investigating the statistical significance of $\hat{\alpha}$.

When household income data are available in a repeated cross-section dataset, we calculate y_{igt}, per-capita real income for individual/household i belonging to cohort group g in year t in the similar manner. We then estimate equation (2) replacing $\log c_{igt}$ by $\log y_{igt}$ and replacing $\bar{\log} c_{gt}$ by $\bar{\log} y_{gt}$ to investigate age effects in within-cohort income inequality. We also estimate equation (2) replacing $(\log c_{igt} - \bar{\log} c_{gt})^2$ by $(\log y_{igt} - \bar{\log} y_{gt})(\log c_{igt} - \bar{\log} c_{gt})$ to investigate age effects in income-consumption correlation.[1]

3 Data

3.1 Thailand

The data source for Thailand is the *Household Socio-Economic Survey* (Thai SES data hereinafter). The Thai SES is conducted by the National Statistical Office of the Government of Thailand. Since 1998, the survey 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.

Ten rounds of Thai SES spanning a period of 19 years (1986, 1988, 1990, 1992, 1994, 1996, 1998, 2000, 2002, 2004) are employed in this paper. The period covered by Thai SES corresponds to a period of the "Asian miracle" from the 1980s to the mid 1990s, the Asian financial crisis of 1997, and finally the recovery from the crisis (Kurita and Kurosaki, 2007). The Thai SES data have a good number of overlapping cohorts across rounds. This is a great advantage in estimating age effects following equation (1) or (2).

Real per-capita consumption (c_{igt}) was calculated by dividing total household consumption expenditure by the number of household members and the consumer price index compiled by the government. Another advantage of the Thai SES is that it includes information on household income. By comparing the dynamics of within-cohort consumption inequality with that of within-cohort income inequality, we can obtain insights regarding factors governing the intertemporal consumption choice of Thai consumers.

Figure 0-2 shows the time series of average log consumption within a cohort for five

[1] Changes in the covariance of log income and log consumption are often utilized to identify sources of income risk (see e.g., Blundell and Preston, 1998).

cohorts. The horizontal axis is the household head's age, as in Figure 0-1. There are two strong trends shown in the left panel of Figure 0-2. First, all cohorts (including those not plotted in the figure) experienced a positive growth in log consumption in their life cycle. This mainly reflects age effects. Second, younger cohorts enjoy higher consumption than older ones, controlling for their age. This mainly reflects the aggregate growth of the Thai economy. There are three periods in which the average log consumption declined, such as from 1986 to 88, from 1996 to 98, and from 1998 to 2000. Nevertheless, the overall trend within a cohort over the life cycle is positive. Indeed, when we estimate an equation similar to (1) but with cohort-average log consumption as the dependent variable, the fitted values of the age fixed effects $\hat{\alpha}_a$, show a very steep growth of consumption.

The right panel of Figure 0-2 investigates the relationship between within-cohort inequality and average consumption. The figure shows very little relationship between the two. From the cohort-level data in Thailand, it seems difficult to find any correlation between the inequality and growth.

3.2 Pakistan

The data source for Pakistan is the *Pakistan Integrated Household Survey* (PIHS) in 1998/99 and 2001/02 and the *Pakistan Social and Living Standards Measurement Survey* (PSLM) in 2004/05 and 2005/06. The PIHS/PSLM data are collected by the Pakistan Federal Bureau of Statistics. While the PIHS is a survey of income and expenditure, the PSLM collects a broader collection of variables related to various aspects of well-being, including income, education, health, *et cetera*. A subsample of households in the PSLM were asked additional questions regarding household income and expenditure surveys; it is data from this subsample which are comparable to similar data from the PIHS.

In each survey, a nationally representative sample was drawn in two stages: primary sampling units (PSU) with different sampling probabilities were randomly chosen in the first stage; twelve (or eleven in the 2005/06 survey) households were randomly chosen from each PSU in the second stage. The sample size for our analysis is approximately 15,000 households in all four surveys, containing approximately 105,000 individuals each year.

In the PIHS/PSLM dataset, nominal consumption expenditure including the imputed values of in-kind transactions per capita[2] in Pakistan Rupees is calculated and then converted into a real term by dividing by the official poverty line. This is the concept known as the "welfare ratio." Since the log variance is employed as the measure of inequality, the unit of measurement does not matter.

[2]To be precise, "per capita" means "per adult equivalence unit," which is the unit adopted by the Government of Pakistan to establish the official poverty line. Individuals who are 18 years old or above are assigned the weight of 1.0 and others are assigned that of 0.8.

The period covered by PIHS/PSLM experienced both increase and decrease of poverty (Kurosaki, 2009). The average consumption declined from 1998/99 to 2001/02, followed by increases in the next two periods. Its level in 2005/06 is only 15% higher than the 1998/99 level but 21% higher than the 2001/02 level. The movement of average consumption is closely related with agricultural production in Pakistan.

3.3 India

For India, we employ data from NSS expenditure surveys, conducted by the National Sample Survey Organization, the Government of India. This paper reports results based on four rounds with so-called "thick" sample: 1983 (38th NSS), 1987/88 (43rd NSS), 1993/94 (50th NSS), and 1999/2000 (55th). The four rounds thus cover about eighteen years. The NSS expenditure dataset contains incredibly detailed information on consumption items.

A great advantage of these NSS datasets is their large sample size. Each round contains approximately 110,000 sample households. This enables us to keep a sufficient number of sample households when we estimate age effects for sub-group levels. On the other hand, NSS surveys do not include information on household income. Therefore, we estimate age effects in within-cohort inequality only for consumption.

The period covered by the four rounds of NSS experienced a continuous decline in poverty. The average per-capita consumption increased continuously during this period, resulting in a decline of poverty head count index from 45% in 1983 to 26% in 1999/2000.[3] However, the level of the poverty measures in 1999/2000 has been debated intensively because consumption modules, especially the recall period, were changed in 1999/2000, resulting in the non-comparability problem. Adjustment to solve the non-comparability problem (like the one implemented by Tarozzi, 2007) is left for further exercise.

4 Empirical Results

In this section, empirical results for the age effects in within-cohort inequality in Thailand, Pakistan, and India are presented. For each country, those estimated from household-level regression (equation (2)) are discussed first: the case when all sample households are pooled, the case when sample households are divided into two groups by their residence (urban vs. rural), and the case when sample households are divided into two groups by the education level of household heads. Then the age effects estimated from cohort-level regression (equation (1)) are discussed to examine the sensitivity to inequality measures, especially to the inequality aversion parameter. To exploit the strengths of each dataset, we add the compar-

[3] Official estimates by the Planning Commission, Government of India.

ison of age effects in consumption inequality versus those in income inequality for the case of Thailand; we add the sensitivity analysis to the household-level controls for the case of Pakistan.

4.1 Thailand

Age effects in consumption and income inequality

Figure 1-1 shows the age effects in the within-cohort variances of logarithms of consumption/income in Thailand. They are estimated using the individual-level regression model of (2) and ten SES rounds from 1986 to 2004. First, the within-cohort consumption inequality increases with age only during very young periods and then gradually declines until retiring ages. This is in sharp contrast to the increasing age-effect reported for developed countries (Deaton and Paxson, 1994; Storesletten et al., 2004). The 95% confidence interval, however, shows that the within-cohort inequality level after the age of mid thirties until the age of late fifties are not significantly different from the inequality level during the early twenties.

On the other hand, the within-cohort inequality in income increases with age sharply during very young periods and then remains constant at that level until retiring ages. The 95% confidence interval shows that the within-cohort inequality level after the age of late twenties until the age of late fifties are significantly higher than the inequality level during the early twenties. This is somewhat similar to the patterns reported for developed countries (Deaton and Paxson, 1994; Storesletten et al., 2004), although the inequality seems to stop rising at the life-cycle stage much earlier in Thailand than in developed countries.

Regional contrast

Figure 1-2 compares the age effects in within-cohort consumption inequality across regions: urban versus rural. An interesting contrast is found. In urban areas, the within-cohort inequality in consumption increases with age steadily until the age of sixties, except for the stagnation in the age of early forties, while in rural areas, the age-effect shows a long period of decline after an initial rise, resulting in a hump shape. In urban areas, the inequality level in the age of late fifties is significantly higher than that in the age of mid twenties, while in rural areas, the opposite holds. The deviation from the pattern observed in developed countries is thus clearer in rural areas. The urban-rural contrast in the age effects exists for within-cohort income inequality as well (not reported). If we plot age effects in income and consumption inequality within cohorts for urban areas only, the shape is quite similar to those reported for developed countries: income inequality increases faster than consumption inequality, suggesting consumption smoothing over the life cycle among urban consumers.

Education contrast

One problem in interpreting the urban-rural contrast is potential endogeneity of rural-urban migration decisions. On the other hand, the educational level of household heads is predetermined for households when they decide on their (dynamic) consumption choices. Figure 1-3, therefore, compares the age effects in within-cohort consumption inequality across education levels. Sample households are divided into a high education group (household heads' years of schooling were more than or equal to 7 years) and a low education group (household heads' years of schooling were less than or equal to 6 years). The contrast is sharper than that in Figure 1-2. The shape for the high education group is similar to that for the urban households while the shape for the low education group shows a clearly declining trend without a hump. However, since the standard error is also large for less educated households, the within-cohort inequality level in consumption is not very significantly smaller than that at the age of 19; it is significantly smaller only after the age of late fifties.

The education contrast in the age effects partially reflects the shape of the age effects in within-cohort income inequality (Figure 1-4 (A)). To make comparison easier, the vertical axis of Figure 1-4 is set equal to that of Figure 1-3. Among the more educated households, the life-cycle shape of income inequality shows a steady increase, whose age slope is steeper than that of consumption inequality. This is similar to observations from developed countries (Deaton and Paxson, 1994; Storesletten et al., 2004). On the other hand, the life-cycle shape of income inequality shows a slight decrease among the less educated households, although the decline is not statistically significant, since the confidence interval is wide. The wide confidence interval seems to suggest that household income among less educated households is subject to larger variation across households that is not explained by household size and fixed effects of age and cohorts. The life-cycle shape of income-consumption correlation (Figure 1-4 (B)) shows a similar pattern, lying between the shape for consumption inequality and that for income inequality. The shape for uneducated households is again in sharp contrast to those found for the US, where the covariance was increasing with age (Blundell and Preston, 1998).

The education contrast we found for consumption inequality among Thai households is also very different from the pattern shown for developed countries. For example, Storesletten et al. (2004, Fig. 2) show that the age effects in consumption inequality among US households are very similar even if the sample is split by the heads' education level into "No high school," "High school," and "College."

Robustness check

The regional and class contrasts shown in these figures are found robustly. First, using individual data and empirical specification (2), we estimated a model without the household size variable,[4] or different specifications of age and cohort fixed effects in terms of intervals, or a specification using a different threshold to divide households into the more and the less educated. We found little change in shapes of the age effects.

Second, we applied the cohort-level regression model (1) to the ten SES rounds from 1986 to 2004 using various inequality measures. In Figure 1-5, we plot results for three inequality measures: Gini coefficient, General entropy measure with parameter 0, and Atkinson's (1970) inequality measure with parameter 1. As shown in this figure, the education contrast becomes sharper when cohort-level data are used: the within-cohort consumption inequality increases with age among the more educated households while it decreases among the less educated households, and the difference is statistically significant. The choice of inequality measures or the choice of empirical models does not affect the results: within-cohort inequality in consumption is decreasing with age among uneducated households.

Regarding the choice of inequality measures, the sensitivity of the analysis with respect to the inequality aversion parameter might be of interest. Figure 1-6 thus shows the case using different parameters for the inequality measure of Atkinson (1970). As shown by Ligon (2008), there is a one-to-one mapping between Atkinson's inequality measures and the constant relative risk aversion utility function, where Atkinson's inequality aversion parameter increases as the coefficient of relative risk aversion increases. As shown in panel (A) of Figure 1-6, the education contrast in age effects in consumption inequality becomes sharper when a higher value of inequality aversion parameter is used. However, some of the change may simply reflect the difference in units rather than the difference in shape. Therefore, in panels (B) and (C), the vertical axis is adjusted using an index (the predicted value of the reference age is set at 100). Since the associated confidence interval is also larger for cases when a higher value of inequality aversion parameter is used, the overall significance levels of the education contrast is similar regardless of the choice of inequality aversion parameters. The difference due to the choice of inequality aversion parameters lies in the age around fifties and sixties among the less educated households: inequality continued to decline if a higher value of inequality aversion is assumed (panel (C)) while it remains somewhat constant if a lower value of inequality aversion is assumed (panel (B)). This seems to suggest that the decrease in consumption inequality among the less educated households occurs more in extreme values of consumption rather than in moderate values of consumption when households are aged.

[4] Robustness check with respect to the expansion of variables X_{igt} is left for further exercise. See the results for Pakistan regarding the robustness check in this direction.

Specification tests using linear age effects

Table 1-1 reports results of specification tests using models with linear age effects (equation (3) or (4)). First, when household-level regression is adopted, the Wald test generally rejects the linear age effect model (4) against the more flexible model with a full set of age fixed effects (2). This is mostly due to the hump shape shown in Figures 1-1 to 1-4. On the other hand, the Wald test does not reject the linear model for less educated households whose age fixed effects are shown in Figures 1-3 and 1-4. Therefore, in these cases, estimating equation (4) is warranted. As shown in the table, $\hat{\alpha}$ is estimated at -0.0035 for consumption inequality, -0.0031 for income inequality, and -0.0016 for income-consumption correlation, all of which are statistically significant. Therefore, the test results clearly support the view that within-cohort inequality and correlation are decreasing over time among the less educated households. In sharp contrast, $\hat{\alpha}$ in equation (4) is significantly positive among the more educated households, although we have to be careful because the specification (4) is rejected against the alternative of specification (2).

When cohort-level regression is adopted, the Wald test generally cannot reject the linear age effect model (3) against the more flexible model with a full set of age fixed effects (1). This is as expected since the age effects shown in Figures 1-5 and 1-6 are approximately linear. The point estimates for $\hat{\alpha}$ in equation (3) are positive among the more educated households while they are negative among the less educated households. Again, the test results robustly supports the view that within-cohort inequality is decreasing over time among the less educated households.

4.2 Pakistan

To investigate the shape of age effects in the within-cohort consumption inequality in Pakistan, equation (2) is estimated using four rounds of PIHS/PSLM from 1998/99 to 2005/06. The Pakistani microdata are associated with uneven intervals and are subject to heaping due to measurement errors in the age and the year of birth reported by the household head. To solve these problems, we employ two-year intervals in defining age and cohort fixed effects. The age fixed effects are based on reported ages (odd ages are rounded-up to the next even age) while the cohort fixed effects are defined on two-year intervals associated with the nearest even intervals in survey years.[5]

[5] Namely, we associated year 1999 with the 1998/99 PIHS, year 2001 with the 2001/02 PIHS, year 2003 with the 2004/05 PSLM, and year 2005 with the 2005/06 PSLM and calculated cohort fixed effects based on these years, with two year intervals. The robustness of our results with respect to this specification is discussed below.

Regional and education contrast

Figure 2-1 shows the age effects in the within-cohort consumption inequality, first for all Pakistan and then distinguishing urban and rural areas. First, the point estimates show an urban/rural contrast similar to the one found in Thailand: the urban pattern is a slight increase while the rural pattern is a flat or slightly decreasing one.[6] This seems to suggest that in Pakistan, urban households' intertemporal choice is quite similar to those in developed countries while households in rural regions behave differently. Second, nevertheless, the age effects are statistically insignificant. In urban areas, the confidence intervals are so wide that the null hypothesis of no change in the within-cohort inequality is not rejected. The wide confidence intervals among urban households suggest that their consumption is subject to a large variation that cannot be explained by age/cohort fixed effects and the household size. In rural areas, the decline in within-cohort inequality is small in absolute values so that they are statistically insignificant.

We then divide sample households by the education status of the household head: a high education group (households with heads who ever entered formal schooling) and a low education group (households with heads who never entered formal schooling), whose results are plotted in Figure 2-2. As in Thailand, the positive slope is observed only among educated households, which is marginally statistically significant. Among the uneducated households, point estimates of age effects show a declining trend, which is statistically significant as well, although marginally. The education contrast in Figure 2-2 shows not only steeper slopes in age effects but also more balanced sizes of confidence intervals than the regional contrast in Figure 2-1.

Robustness check

The education contrast was found robustly for Pakistan as well. In Figure 2-3, the sensitivity of our results with respect to household-level control variables X_{igt} in equation (2) is investigated. Figure 2-2 using the household size as the only household-level control is re-produced in panel (A) of the figure. Although the household size is statistically significant in most of the regression results, its elimination does not affect much the shape of the figure, as shown in panel (B) of Figure 2-3. When we added more controls, namely, linear terms of five demographic variables and the regional fixed effects (province dummies and urban/rural dummies), the education contrast becomes less significant, although the point estimates still show that the age effect in within-cohort consumption inequality is positive

[6] This contrast is confirmed when we compare the urban regions in Sindh and Punjab (two provinces out of four in Pakistan, known as more developed regions) versus the rural households in Sindh. The pattern in rural Sindh is a slight decrease while the one in urban Punjab and Sindh is a steady increase. See also Kurosaki (2009) for similar contrasts between urban Sindh/Punjab and rural Sindh.

among educated households while it is negative among uneducated households (panel (C) of Figure 2-3). Unfortunately, in panel (C), two confidence intervals are overlapping, making it difficult to reject the null that the age effects are the same between educated and uneducated households. Since many of the variables added in X_{igt} for panel (C) of Figure 2-3 are presumably endogenous to households' decision making, we prefer specification (A) or (B) to (C).

The finding that the age effect in within-cohort consumption inequality is positive among educated households while it is negative among uneducated households was confirmed when age effects were identified against round fixed effects instead of against cohort fixed effects (not reported). Different intervals to define age and cohort fixed effects were also attempted to examine the robustness of our results. The results using one year intervals for both age and cohort fixed effects (corresponding to the actual survey years), or three year intervals for both age and cohort fixed effects (corresponding to the nearest 3-year equal intervals in survey years) resulted in qualitatively the same results. We also attempted other thresholds to classify households into more and less educated households. Under the threshold used to generate Figures 2-2 and 2-3, sample households are divided into two halves with very similar size. Among those household heads who ever entered formal schooling, about one fifth dropped out from primary school without completing the first stage of primary education. When we use the threshold line of "primary (fifth grade) or better" versus "less than fifth grade completion," the results are very similar to Figures 2-2 and 2-3, with similar statistical inference. When we further upgrade the threshold line at "more than primary (fifth grade)" versus "equal to or less than fifth grade," the education contrast become insignificant.

Using the PIHS/PSLM data, age effects in the variances of logarithms of income were also estimated. To our disappointment, the estimated age effects are very unstable, yielding different shapes depending on specifications. Not only the signs of trends changed depending on specifications, but the absolute size of the age effects also changed by a factor of ten. It seems that income data in PIHS/PSLM suffer from frequent misreporting or nonreporting. Because of this reason, age effects of within-cohort income inequality in Pakistan are not reported in this paper.

The education contrast remains intact when we estimate the cohort-level regression model (1) using the cohort-level data calculated from the four PIHS/PSLM rounds. However, this contrast holds for the point estimates only. The estimated confidence intervals are wide for both educated and uneducated households except for a few inequality measures for which the increasing inequality among the educated is marginally significant at a later stage of life. Figure 2-4 reports the results when various parameters are used for Atkinson's inequality measures. Age effects among educated households show a slight increase while those among uneducated households show no trend. In all three cases plotted in Figure 2-4, confidence intervals are so wide that no statistical inference is possible.

Specification tests using linear age effects

The results of specification tests for linear age effects (equation (3) or (4)) against more flexible age fixed effects (equation (1) or (2)) for Pakistan (Table 2-1) are qualitatively similar to those for Thailand (Table 1-1). When household-level regression is adopted, the Wald test generally rejects the linear age effect model, while when cohort-level regression is adopted, the Wald test generally cannot reject the linear age effect model against the more flexible model. When the restricted model with the linear age effects is adopted, the regional and the education contrast becomes statistically significant. For instance, $\hat{\alpha}$ is estimated at 0.0049 among urban households and 0.0060 among educated households, both of which are statistically significant, while $\hat{\alpha}$ is not significantly different from zero among rural or uneducated households. When no household-level control is used, $\hat{\alpha}$ becomes significantly negative among uneducated households. The education contrast remains significant when cohort-level regression models are employed.

This exercise shows that, even with a dataset whose length of period covered by the surveys is short, like the one from Pakistan, the education contrast can be shown with statistical significance if we are ready to impose more structures on age effects in inequality. The finding for Pakistan that age effects among educated households show an increase while those among uneducated households show no or a slightly negative trend thus seems robust.

4.3 India

Regional and education contrast

Figure 3-1 shows the age effects in the within-cohort variances of log consumption in India, focusing on the urban/rural contrast, estimated by equation (2). Similar to the case of Pakistan, the Indian microdata are taken from four rounds with uneven intervals and are subject to heaping due to measurement errors in the age/birth year reported by the household head. When we attempted age and cohort fixed effects defined on one-year intervals, the resulting age effects were severely affected by the heaping. When we employed two-year or longer intervals, the effects of heaping were mitigated. Therefore, we report results estimated with age fixed effects defined on two-year intervals and cohort fixed effects defined on five-year intervals associated with the nearest 5-year equal intervals in survey years.[7] When we use all households, the within-cohort inequality is slightly decreasing and the inequality

[7]Namely, we associated year 1984 with the 38th NSS, year 1989 with the 43rd NSS, year 1994 with the 50th NSS, and year 1999 with the 55th NSS and calculated cohort fixed effects based on these years, with five year intervals.

level in the later ages is significantly smaller than that in the age of early twenties. This is similar to the finding in Thailand and again in sharp contrast to the increasing age-effect reported for developed countries (Deaton and Paxson, 1994; Storesletten et al., 2004). Across regions, the declining age effects on within-cohort inequality are strongly observed among rural households. Among urban households, the within-cohort inequality declines with age but at a slower pace, while among rural households, it decreases rapidly with a relatively narrow confidence intervals. The deviation from the pattern observed in developed countries is thus clearer in rural areas, as in Thailand. The confidence intervals are narrower among rural households than among urban households, which is similar to the Pakistani case but opposite to the Thai case.

As a more exogenous variable to classify sample households, Figure 3-2 shows the age effects in the within-cohort consumption inequality, focusing on the education contrast. Sample households are divided into a high education group (household heads' years of formal schooling were more than one: "ever" been to school) and a low education group (household heads had never been enrolled in formal schooling). This threshold is the same as the one adopted for the Pakistani case. As in the cases of Thailand and Pakistan, the education contrast is sharper than the regional contrast in Figure 3-1. The confidence interval is also narrower when we use the education contrast. Because of this, unlike the case of Thailand, the decreasing age effects among less educated households are highly significant. Thanks to the very large sample size of India's NSS, we are thus able to show a case with statistically significant decline in age affects in within-cohort inequality.

Robustness check

The regional and class contrasts shown in these figures are robustly found. First, using individual data and empirical specification (2), we estimate models with different specifications of age and cohort fixed effects in terms of intervals or a specification using a different threshold to divide households into the more and the less educated. Regarding the former, the use of one year intervals for both age and cohort fixed effects resulted in a severe heaping problem, as already noted. On the other hand, other intervals worked well: we attempted age fixed effects in two or three or five years intervals; cohort fixed affects with five-year intervals associated with the nearest even intervals in survey years, or, fixed effects with three-year intervals using the actual years of survey. The results were very similar to those reported in Figures 3-1 and 3-2. Regarding the latter, the education contrast becomes less sharp (but still statistically significant) when households educated more than primary (fifth grade) are compared with others. Since a substantial number of household heads had never entered formal schooling in India, the threshold reported in Figure 3-2 is a more natural choice.

Second, we estimate the cohort-level regression model (1) using the cohort-level data calculated from the four NSS rounds. This approach has an advantage of using various inequality measures. The results robustly support the shape of Figures 3-1 and 3.2, regardless of the choice of inequality measures.[8] As an example, panel (A) of Figure 3-3 shows the cohort-level regression results when Atkinson's inequality measure with parameter one is employed. The within-cohort inequality is associated with little age effects among the educated households while it is associated with significantly negative age effects among the uneducated households. As in Thailand, the decline of inequality among the less educated becomes sharper and steeper when the inequality aversion parameter is increased (compare panel (B) and (C) of Figure 3-3). The confidence intervals are reasonably narrow even when we use the cohort-level data. This is in sharp contrast to the case of Pakistan. Both Indian and Pakistani datasets come from four rounds of repeated-cross section microdata. However, the period covered by the Indian data is much longer (eighteen years) than that by the Pakistani data (seven years). Because of this difference, the overlapping of cohorts is thicker in the Indian data, resulting in better identification of age effects.

Specification tests using linear age effects

Table 3-1 reports specification test results for India. First, when household-level regression is adopted, the Wald test generally rejects the linear age effect model (4) against the more flexible model with a full set of age fixed effects (2). When cohort-level regression is adopted, the Wald test strongly rejects the linear age effect model (3) against the more flexible model with a full set of age fixed effects (1) for the less educated households, but it cannot reject it for the more educated households.

Therefore, we have to be careful in interpreting the estimated coefficient $\hat{\alpha}$. Nevertheless, the point estimates for α (slope in the linear model) confirm the education contrast: In all four pairs shown in Table 3-1 comparing more and less educated households, the slope among the less educated is more negative than that among the more educated and the difference was statistically significant at the 1% level. Unlike Thailand and Pakistan, $\hat{\alpha}$ is negative even among the more educated households with statistical significance. However, their magnitude is much smaller than that among the less educated households. This is what we focus on as the basic education contrast.

[8] Details are available on request. See also the results reported by Kurita (2005), who found a very strong contrast depending on the education levels of household heads using Gini coefficients.

5 Theoretical Interpretations

The results in the previous section show that within-cohort consumption inequality does not increase as households get older in various cases from developing countries. The deviation from the increasing pattern is especially significant among less educated households. This finding thus suggests that the applicability of the permanent income hypothesis with perfect credit markets (PIH-UC) is not very high for these cases. Theoretically, several alternative models of intertemporal choice under risk are proposed in the literature and some authors (e.g., Fafchamps, 2003, Chapter 5) explicitly discuss their implications to inequality in developing countries.

First, as a benchmark, the model of full risk-sharing (or Arrow-Debreu complete markets model) achieves more efficient resource allocation than the PIH-UC model. Under this model, idiosyncratic shocks to income are fully insured so that they should not affect consumption at all (Townsend, 1994; Kurosaki, 2001). This implies that, if households have homogenous time preferences, the age effect in consumption inequality remains flat regardless of the dynamics of income inequality.

Another useful benchmark is the model of autarky with no saving technology. Under this model, households always consume their income without any intertemporal or interstate resource allocation. Therefore, the consumption inequality dynamics should closely track the income inequality dynamics.

Between the two polar cases of benchmarks lies the model of PIH-UC. Under PIH-UC, idiosyncratic shocks to income affect consumption partially so that the consumption inequality is moderately increasing, when income inequality dynamics shows an increasing pattern (Deaton and Paxson, 1994). By incorporating credit constraints (e.g., Deaton, 1991), the PIH-UC model can be extended in the direction of the autarky model. Between the two polar cases of the full risk-sharing model and the autarky model also lie models of risk-sharing under private information (Ligon, 1998; Kocherlakota and Pistaferri, 2007) and risk-sharing with limited commitment (Ligon et al., 2002; Krueger and Perri, 2006).

Another dimension that should affect consumption dynamics is the possibility of misspecification of preferences. As Deaton and Paxson (1994) pointed out, the prediction that the inequality in consumption increases with age is based on the assumption that preferences across individuals and across the family cycle are homogeneous. When heterogeneity is allowed, we cannot obtain an unambiguous prediction regarding the relation between inequality and age.[9] Regarding preference misspecification, a sort of lexicographic consumption pref-

[9]Consider the case of full risk-sharing among households with heterogenous time preferences. As Kurosaki (2001) shows theoretically, under the Pareto-optimal consumption allocation, those households with higher subjective discount rates should be allocated more consumption in earlier periods than other households.

erence could also imply decreasing consumption inequality. Suppose that households first attempt to satisfy "Subsistence consumption" consisting of minimum food and minimum non-food (like basic education). As uneducated households cannot afford non-subsistence consumption, their within-cohort consumption inequality can be associated with negative age effects, if basic education expenditure and minimum food needs are very heterogenous among relatively young households. Once households can satisfy "Subsistence consumption," they spend their money on "Non-subsistence consumption" which follows the standard consumer model associated with positive age effects. The positive age effects are thus substantial only among urban/educated households. To investigate the validity of this model, we distinguished various types of consumption categories and re-estimated the age effects, to examine whether the odd age-effects would disappear when non-subsistence consumption is used. Preliminary results showed that this was not the case.[10]

The decreasing age effect in consumption inequality within cohort, found widely in low-income regions and classes in Asia, seem to be consistent with partial insurance models under conditions that are different from those in developed countries. The first of such cases could be partial insurance models (or the autarky model with no storage technology) associated with within-cohort income inequality decreasing with age. It is trivially true that the consumption inequality should be decreasing with age under the autarky model with no storage technology, when the income inequality decreases with age. Under partial insurance models, if the within-cohort income inequality is increasing with age or constant across age, the consumption inequality should be increasing with age. Therefore, only when the speed of decrease in the income inequality is sufficiently high, we can expect consumption inequality to decrease with age under partial insurance models. Rural and uneducated households are poorer on average than educated or urban households, with limited opportunity to spread risk over time or space, resulting in partial insurance at best and the autarky at worst. The decreasing income inequality could occur in agriculture-based rural societies—since agricultural income is subject to weather and other exogenous shocks, most of which are transitory, the accumulation of permanent shocks in productivity is negligible; on the other hand, when a household is young in its life cycle, agricultural skills are more uncertain (associated with larger variance of transient farm income) and the household head may try several employ-

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This implies that consumption inequality should be decreasing within cohort under full risk-sharing, if poorer households have lower discount rates than richer households. However, the usual claim about poverty is the opposite: poorer households are more likely to have higher discount rates than richer households, if there is heterogeneity in time preferences. Furthermore, the actual consumption allocation in Indian villages was not found responsive to potential differences in discount rates (Kurosaki, 2001). For these reasons, the possibility of full risk-sharing with poor and patient households is ruled out in the discussion below.

[10] These preliminary results could be due to ill-identification of non-subsistence consumption, because the key idea here is to include some non-food consumption as "subsistence". This is worth further investigation.

ment opportunities outside agriculture. These may lead to larger heterogeneity in income earnings when the household head is young. Figure 1-4 (A) is consistent with this story, although the negative trend was weak.

The second of such cases could be partial insurance models (either due to limited commitment or due to private information) with increasing efficiency as households get older. It is plausible that the uneducated and aged in villages may have less information asymmetry problems after repeated transactions; the value of mutual insurance may be increasing with age; the enforcement mechanisms against renege may be improving with age. If one of these holds, the efficiency level of insurance improves as households become older under the partial insurance models. If this is the case, we should observe a decreasing age effects not only in within-cohort consumption inequality but also in within-cohort income-consumption correlation, since the individual-level income-consumption link becomes weaker as risk-sharing becomes more efficient. Figure 1-4 (B) is consistent with this story, although the negative trend was weak.

However, these are only a conjecture. We first need to collect more evidence for the decreasing within-cohort consumption inequality. The evidence shown in this paper may not be strong enough, suffering from statistical insignificance in several cases when the number of survey rounds is small or the length of period covered by the surveys is short.[11] After the evidence is accumulated, more rigorous tests to identify the relevant model will be conducted. In such tests, the appropriateness of alternative models, such as risk-sharing under private information, risk-sharing under limited commitment, and more flexible specifications of preference, should also be considered. Rigorous modeling and statistical tests for the appropriate model of household's consumption dynamics are left for further research.

[11] We also need to refute other possibilities such as that fertility decisions are substantially different for educated and uneducated households, and differences in household composition are not adequately dealt with by the conversion to adult equivalences and the inclusion of household size as an explanatory variable in the household-level regression model; or that high growth households in these countries may have selected out of the surveys.

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Table 1-1. Specification tests using linear age effects, Thailand

(A) Household-level regression	Wald test of (4) against (2)		Coefficient of alpha in (4)	
	Statistics	Value	Coef.	S.E.
Figure 1-1: All Thailand				
Consumption	F(24,192006)	4.55 ***	-0.00288	0.00041 ***
Income	F(24,192006)	5.61 ***	-0.00053	0.00058
Figure 1-2: Consumption				
Urban areas	F(24,113674)	2.98 ***	0.00148	0.00049 ***
Rural areas	F(24, 78271)	1.69 **	-0.00351	0.00055 ***
Figure 1-3: Consumption				
More educated	F(24, 76839)	3.45 ***	0.00187	0.00074 **
Less educated	F(24,114882)	1.29	-0.00352	0.00041 ***
Figure 1-4 (A): Income				
More educated	F(24, 76839)	3.05 ***	0.00879	0.00108 ***
Less educated	F(24,114882)	0.84	-0.00307	0.00058 ***
Figure 1-4 (B): Income/Consumption correlation				
All Thailand	F(24,192006)	4.90 ***	-0.00083	0.00043 *
More educated	F(24, 76839)	3.42 ***	0.00455	0.00455 ***
Less educated	F(24,114882)	0.81	-0.00162	0.00041 ***
(B) Cohort-level regression	**Wald test of (3) against (1)**		**Coefficient of alpha in (3)**	
	Statistics	Value	Coef.	S.E.
Figure 1-5: Consumption, General entropy with parmeter 0				
More educated	F(24, 200)	1.34	0.00236	0.00047 ***
Less educated	F(24, 200)	1.22	-0.00227	0.00046 ***
Figure 1-5: Consumption, Atkinson with parameter 1				
More educated	F(24, 200)	1.42	0.00187	0.00037 ***
Less educated	F(24, 200)	1.32	-0.00184	0.00038 ***
Figure 1-6 (B): Consumption, Atkinson with parameter 0.5				
More educated	F(24, 200)	1.25	0.00136	0.00022 ***
Less educated	F(24, 200)	1.49 *	-0.00086	0.00023 ***
Figure 1-6 (C): Consumption, Atkinson with parameter 2				
More educated	F(24, 200)	1.63 **	0.00148	0.00057
Less educated	F(24, 200)	1.04	-0.00332	0.00057 ***

Source: Estimated by the authors from Thai SES data (10 rounds from 1986 to 2004).

Table 2-1. Specification tests using linear age effects, Pakistan

(A) Household-level regression	Wald test of (4) against (2)		Coefficient of alpha in (4)	
	Statistics	Value	Coef.	S.E.
Figure 2-1: Consumption inequality				
All Pakistan	F(24, 56183)	2.53 ***	0.00379	0.00094 ***
Urban areas	F(24, 21931)	1.73 **	0.00494	0.00182 ***
Rural areas	F(24, 34197)	2.92 ***	-0.00004	0.00082
Figure 2-2: Consumption inequality				
More educated	F(24, 29573)	1.33	0.00600	0.00138 ***
Less educated	F(24, 26555)	1.74 **	-0.00135	0.00086
Figure 2-3: No household-level control				
More educated	F(24, 29574)	1.13	0.00437	0.00138 ***
Less educated	F(24, 26556)	1.74 **	-0.00138	0.00085 *
Figure 2-3: Full controls of demographic and regional controls				
More educated	F(24, 29565)	1.50 *	0.00239	0.00142 *
Less educated	F(24, 26547)	1.74 **	-0.00083	0.00090
(B) Cohort-level regression	Wald test of (3) against (1)		Coefficient of alpha in (3)	
	Statistics	Value	Coef.	S.E.
Figure 2-4 (A): Consumption, Atkinson with parameter 1				
More educated	F(24, 50)	0.50	0.00349	0.00156 **
Less educated	F(24, 50)	0.44	0.000003	0.00100
Figure 2-4 (B): Consumption, Atkinson with parameter 0.5				
More educated	F(24, 50)	0.48	0.00218	0.00108 **
Less educated	F(24, 50)	0.43	0.00021	0.00066
Figure 2-4 (C): Consumption, Atkinson with parameter 2				
More educated	F(24, 50)	0.50	0.00460	0.00185 **
Less educated	F(24, 50)	0.48	-0.00063	0.00139

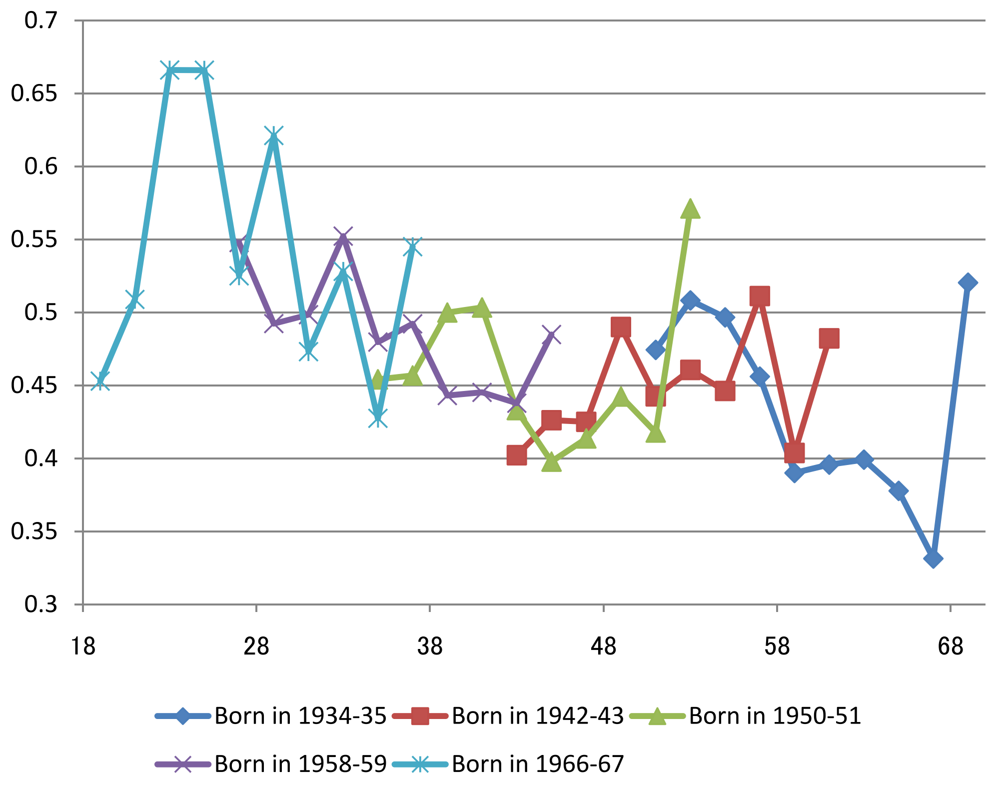
Source: Estimated by the authors from Pakistan's PIHS/PSLM data.

Table 3-1. Specification tests using linear age effects, India

	Wald test of (4) against (2)			Coefficient of alpha in (4)		
(A) Household-level regression	Statistics	Value		Coef.	S.E.	
Figure 3-1: Consumption						
All India	F(24,435452)	9.77	***	-0.00341	0.00016	***
Urban areas	F(24,159873)	6.64	***	-0.00279	0.00029	***
Rural areas	F(24, 275538)	7.40	***	-0.00457	0.00016	***
Figure 3-2: Consumption						
More educated	F(24, 198195)	12.54	***	-0.00227	0.00026	***
Less educated	F(24,237216)	8.96	***	-0.00559	0.00016	***
(B) Cohort-level regression	Wald test of (3) against (1)			Coefficient of alpha in (3)		
	Statistics	Value		Coef.	S.E.	
Figure 3-3 (A): Consumption, Atkinson with parameter 1						
More educated	F(24, 68)	0.40		-0.00066	0.00022	***
Less educated	F(24, 68)	4.40	***	-0.00209	0.00015	***
Figure 3-3 (B): Consumption, Atkinson with parameter 0.5						
More educated	F(24, 68)	0.40		-0.00035	0.00013	***
Less educated	F(24, 68)	3.12	***	-0.00112	0.00085	***
Figure 3-3 (C): Consumption, Atkinson with parameter 2						
More educated	F(24, 68)	0.60	**	-0.00115	0.00032	***
Less educated	F(24, 68)	7.10	***	-0.00365	0.00025	***

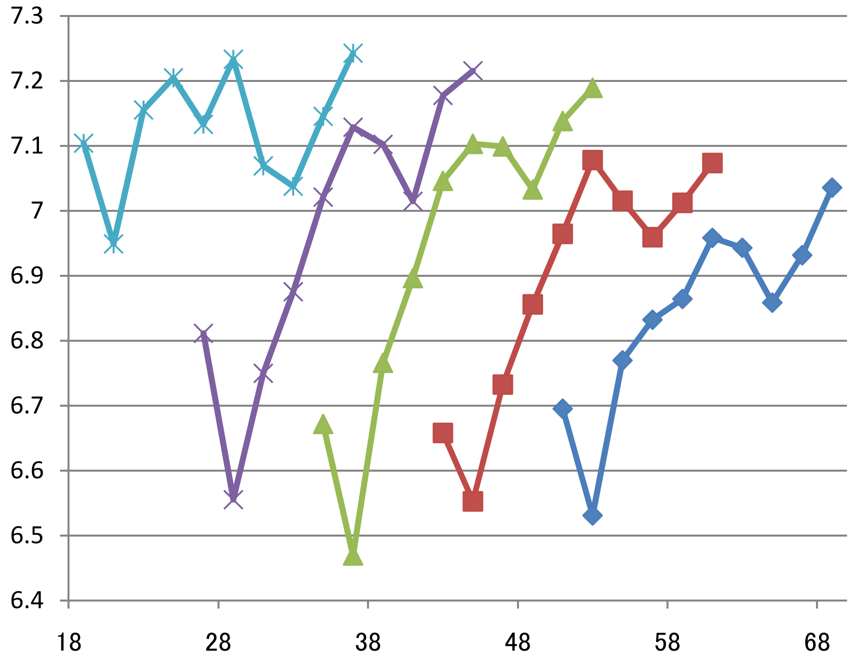
Source: Estimated by the authors from India NSS data (4 rounds from 1983 to 2000).

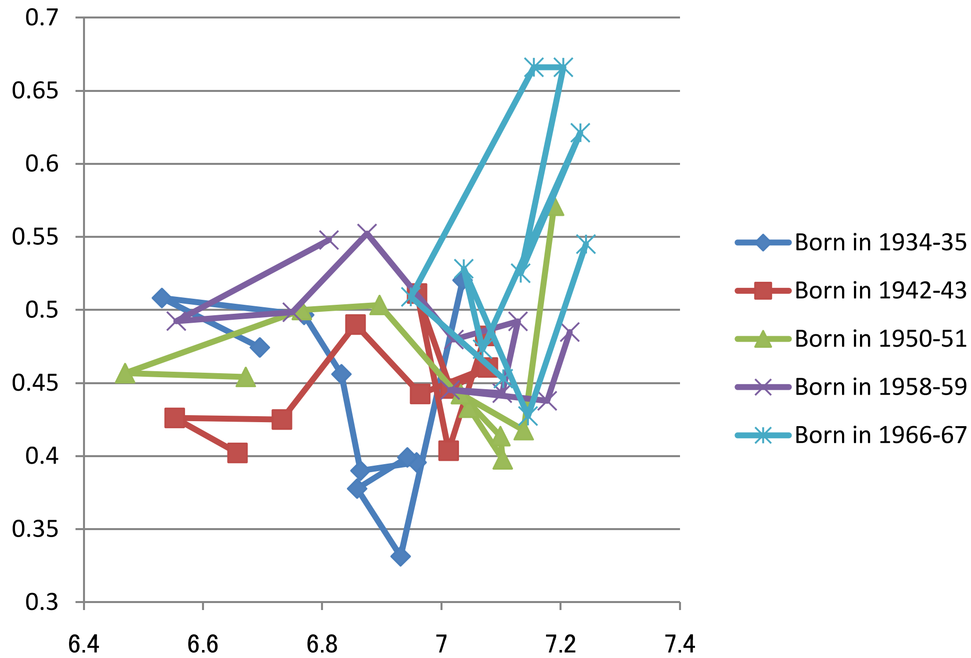
Figure 0-1. Within-cohort inequality of consumption in Thailand, 1986-2004



Horizontal axis: age of the household head.
Vertical axis: Observed values of inequality measures (variances of log consumption)
Source: Compiled from Thai SES data (10 rounds from 1986 to 2004), age and cohorts in 2-year intervals.
To improve readability, data for five cohorts selected with 8 years of intervals are plotted, omitting three cohorts inbetween. For example, the light blue plots show inequality measures for the cohort whose household heads were born in 1966 and 67; the first light blue plot was observed in the 1986 survey while the last plot was observed in the 2004 survey.

Figure 0-2. Inequality versus growth of consumption in Thailand, 1986-2004

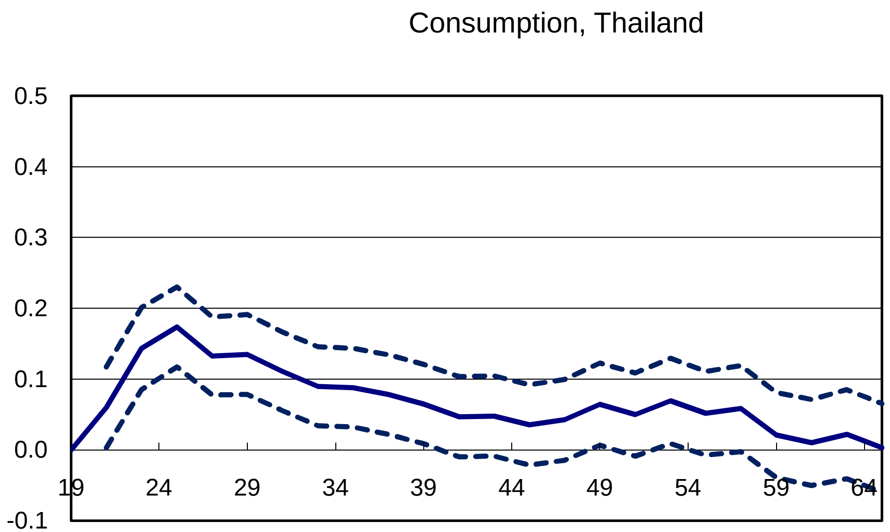


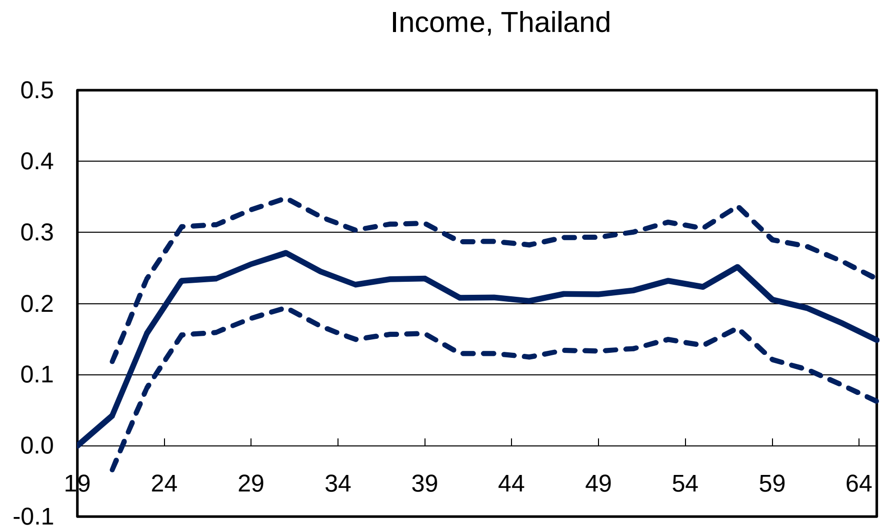


Horizontal axis: age of the household head.
Vertical axis: Observed values of average log consumption for each cohort.

Horizontal axis: Observed values of consumption level (average log consumption)
Vertical axis: Observed values of inequality (variances of log consumption)

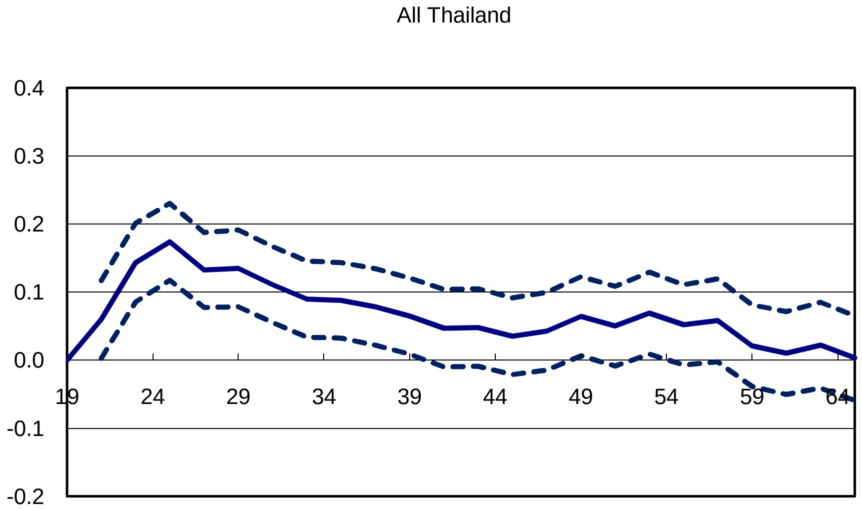
Figure 1-1. Age effects in the variances of logarithms of consumption/income in Thailand



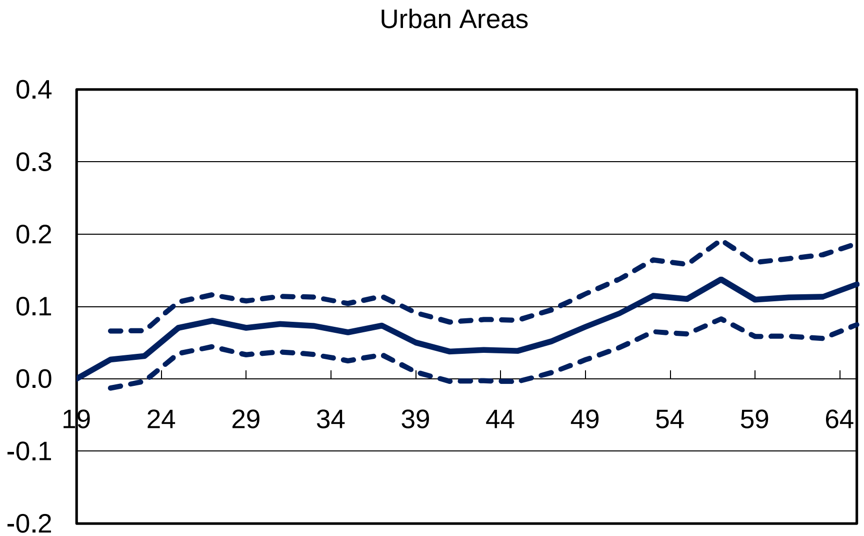


Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=19 as reference)
Source: Estimated from Thai SES data using weighted regression to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 19 to 69.
Use 10 rounds from 1986 to 2004, age and cohorts in 2-year intervals.
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 192,067.

Figure 1-2.
Age effects in consumption inequality and regions, Thailand



Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=19 as reference)
Source: Estimated from Thai SES data using weighted regression
to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 19 to 69.
Use 10 rounds from 1986 to 2004, age and cohorts in 2-year intervals.
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 113,735 for urban areas; 78,332 for rural areas.



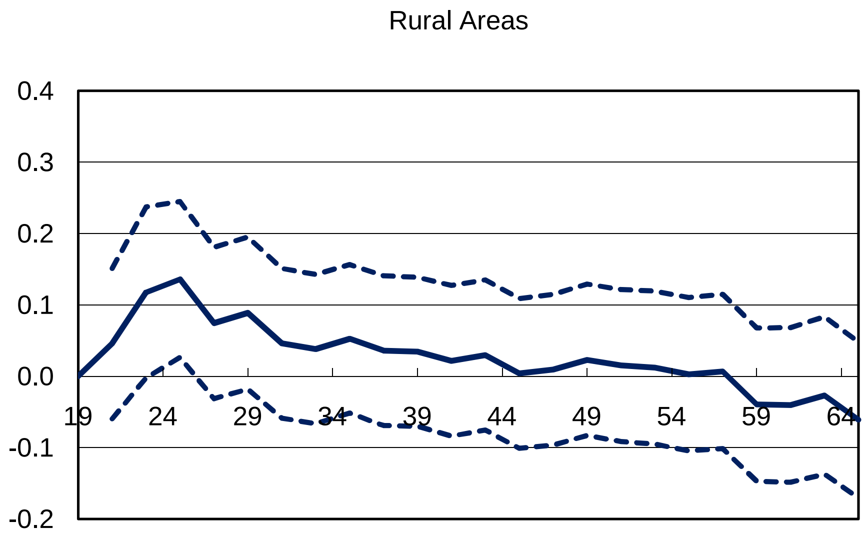
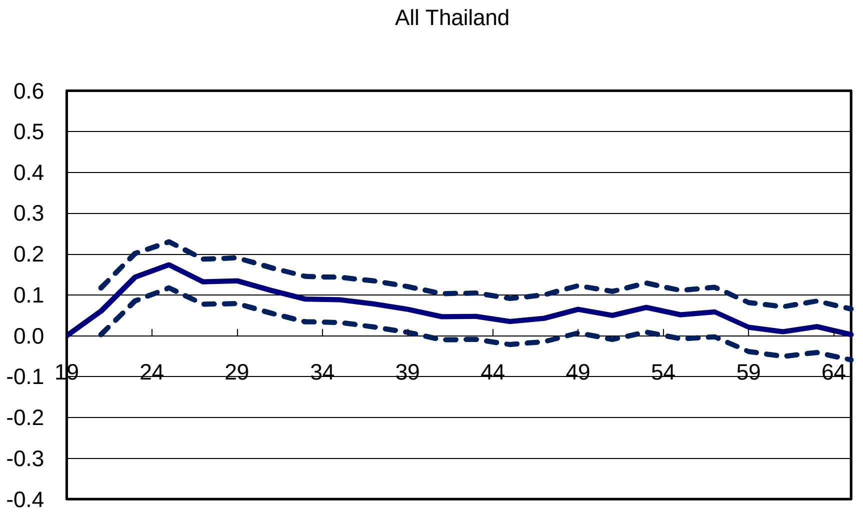
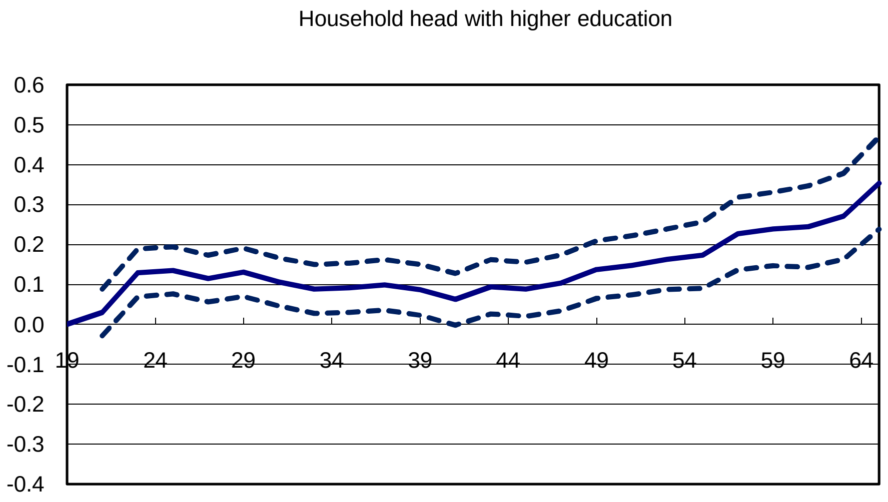


Figure 1-3.
Age effects in consumption inequality and education, Thailand

Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=19 as reference)
Source: Estimated from Thai SES data using weighted regression
to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 19 to 69.
Use 10 rounds from 1986 to 2004, age and cohorts in 2-year intervals.
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 76,900 for the more educated; 114,943 for the less educated.





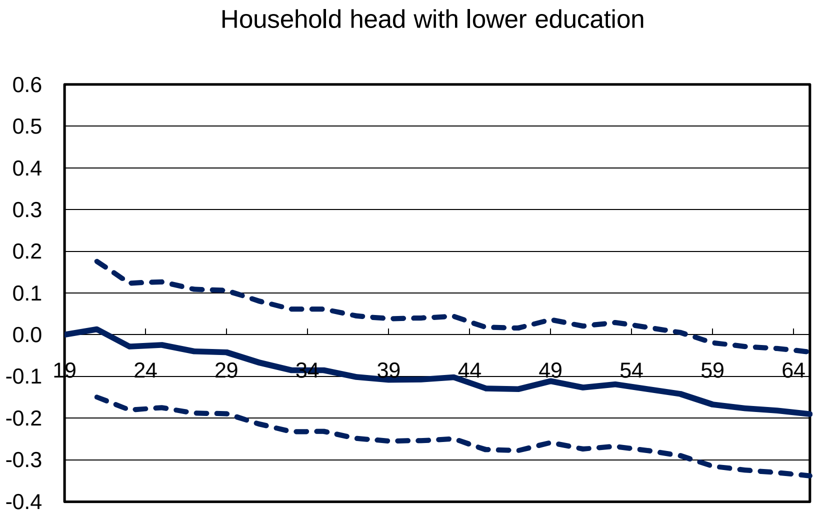
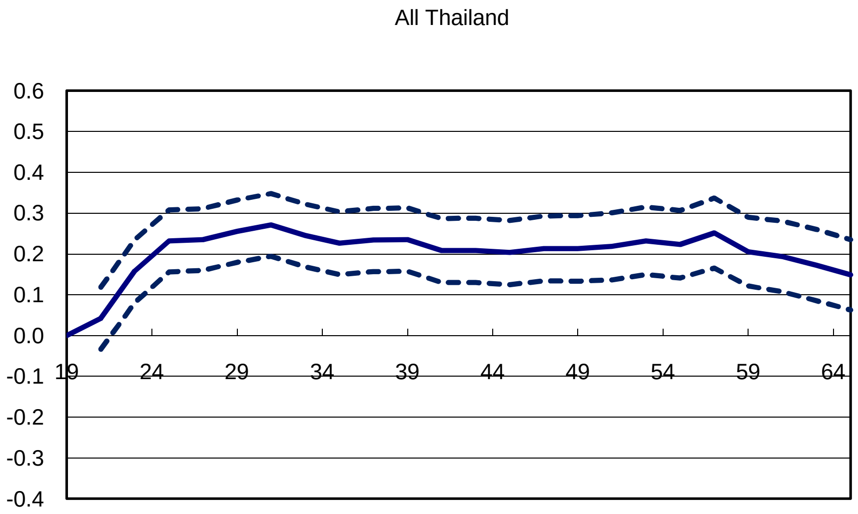
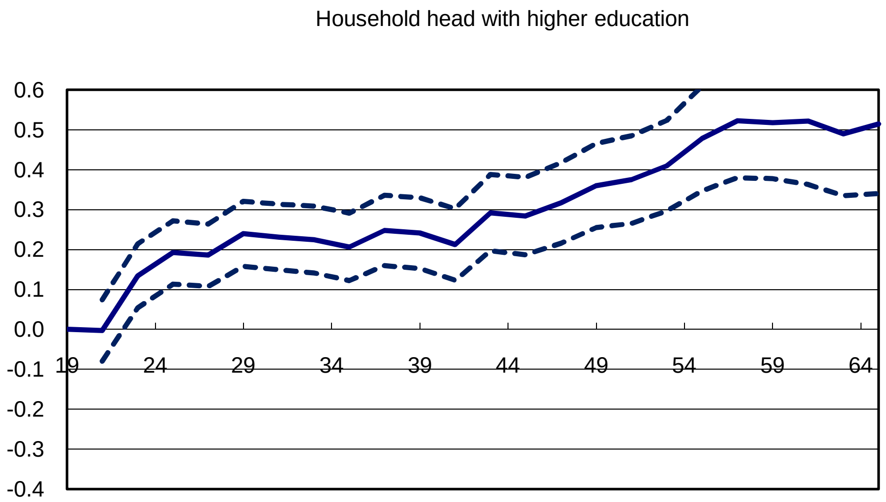


Figure 1-4 (A).
Age effects in income inequality and education, Thailand



Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=19 as reference)
Source: Estimated from Thai SES data using weighted regression
to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 19 to 69.
Use 10 rounds from 1986 to 2004, age and cohorts in 2-year intervals.
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 76,900 for the more educated; 114,943 for the less educated.



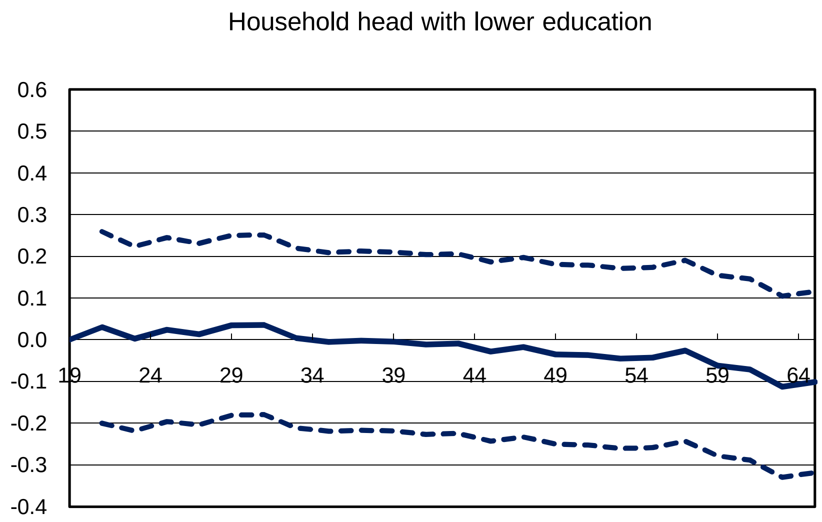
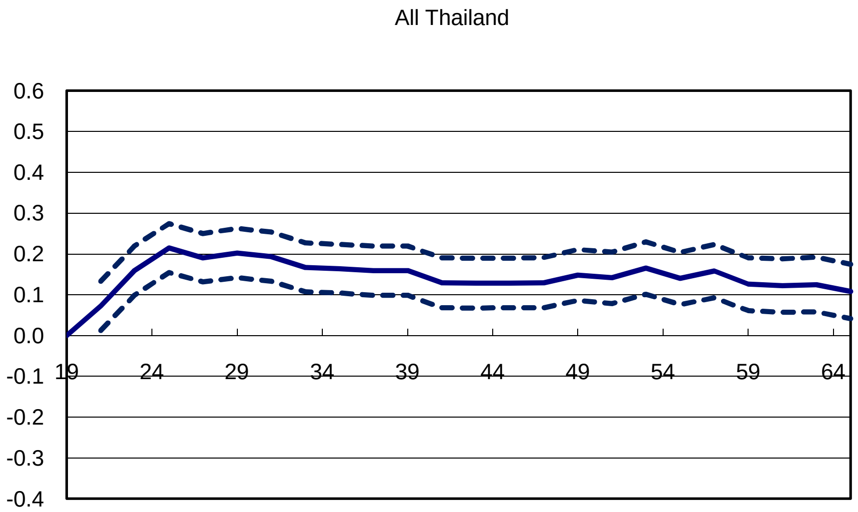
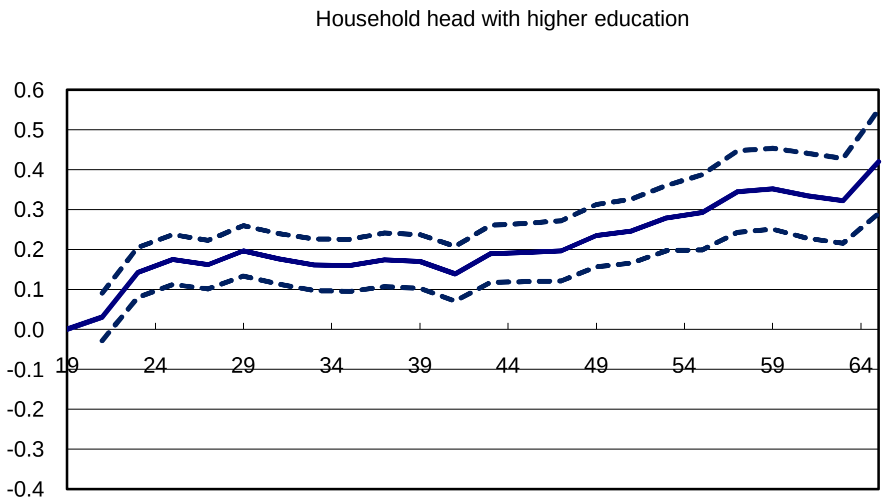


Figure 1-4 (B).
Age effects in income/consumption correlation and education, Thailand

Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=19 as reference)
Source: Estimated from Thai SES data using weighted regression
to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 19 to 69.
Use 10 rounds from 1986 to 2004, age and cohorts in 2-year intervals.
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 76,900 for the more educated; 114,943 for the less educated.





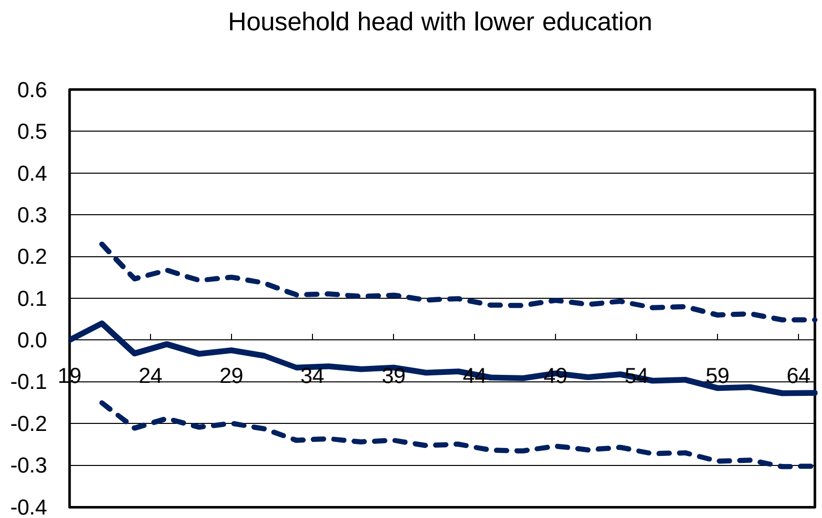
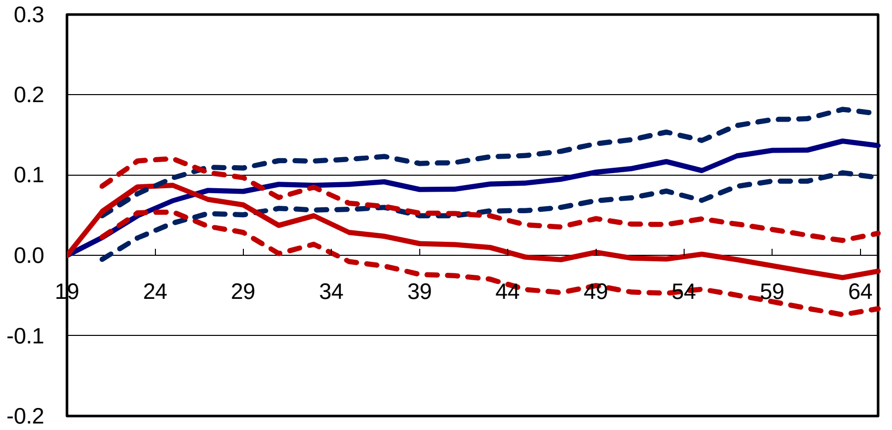


Figure 1-5.
Age effects in consumption inequality using cohort-level data, Thailand

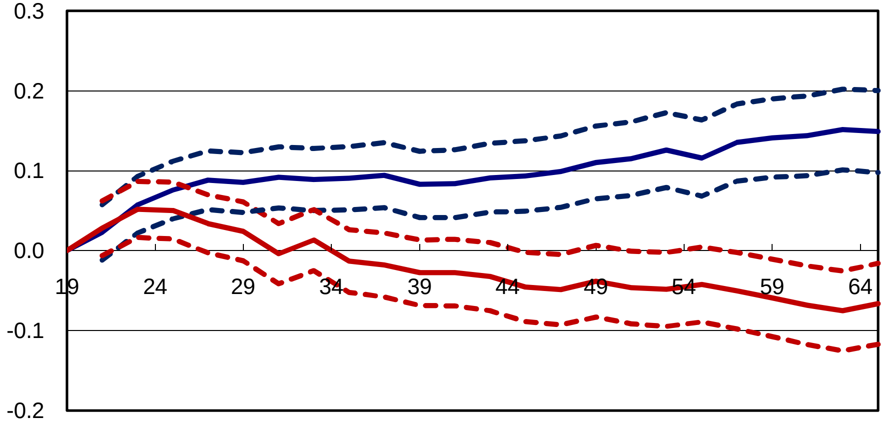
Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=19 as reference)
Source: Estimated from Thai SES data by OLS.
Cohort-level data, hh head's age in the range from 19 to 69.
Use 10 rounds from 1986 to 2004, age and cohorts in 2-year intervals.
NOB=260.

Violet: Household head with higher education
Red: Household head with lower education

Gini coefficient



General entropy with param.0



Atkinson with param.1

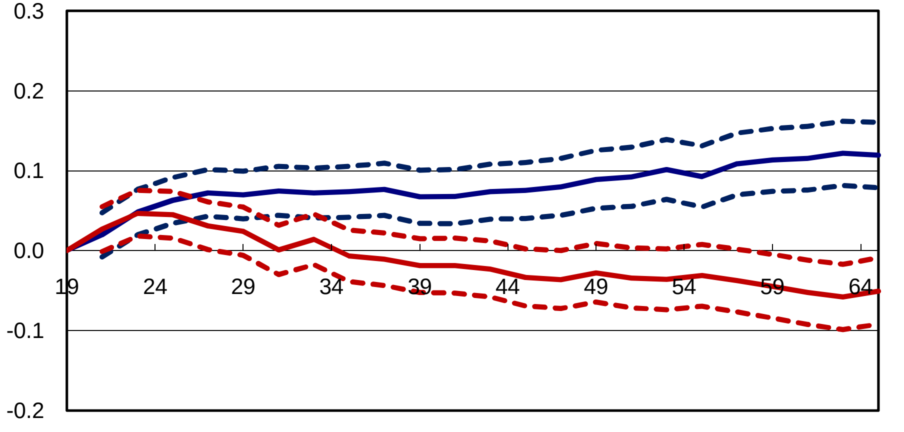
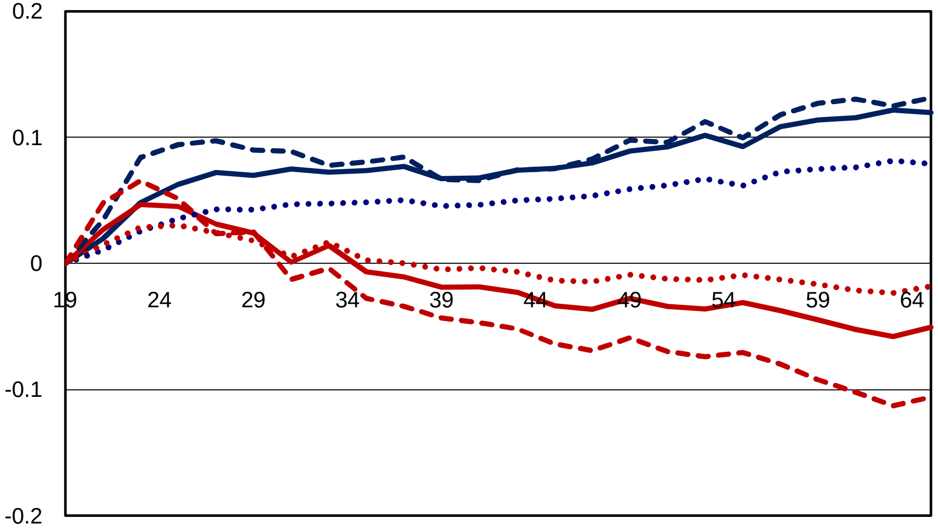


Figure 1-6.
Education contrast in age effects in consumption inequality and inequality aversion parameter, Thailand

(A) Point estimates for different inequality aversion parameters



Horizontal axis=age of the household head.
Source: Estimated from Thai SES data by OLS.
Cohort-level data, hh head's age in the range from 19 to 69.
Use 10 rounds from 1986 to 2004, age and cohorts in 2-year intervals.
NOB=260.

Violet: Household head with higher education
Red: Household head with lower education

(A) Inequality aversion parameter for the Atkinson inequality measures:

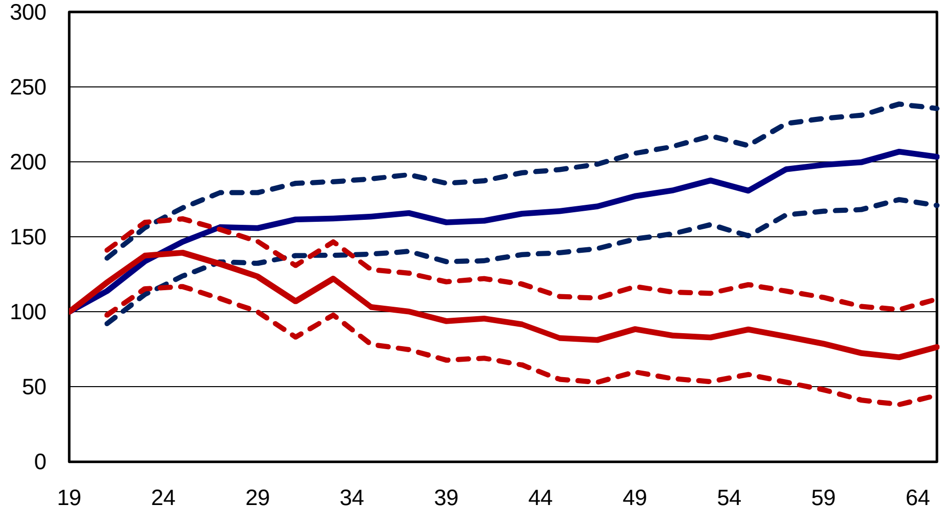
Vertical axis: Coeff. on AGE f.e. (Age=19 as reference)

Dot lines: parameter = 0.5 (least inequality-averse)
Usual lines: parameter = 1
Dashed lines: parameter = 2 (most inequality-averse)

(B) & (C): Dashed lines show 95% confidence interval.

Vertical axis: Index using the predicted value for Age=19 (reference) as 100

(B) Parameter = 0.5 (less inequality-averse)



(C) Parameter = 2 (more inequality-averse)

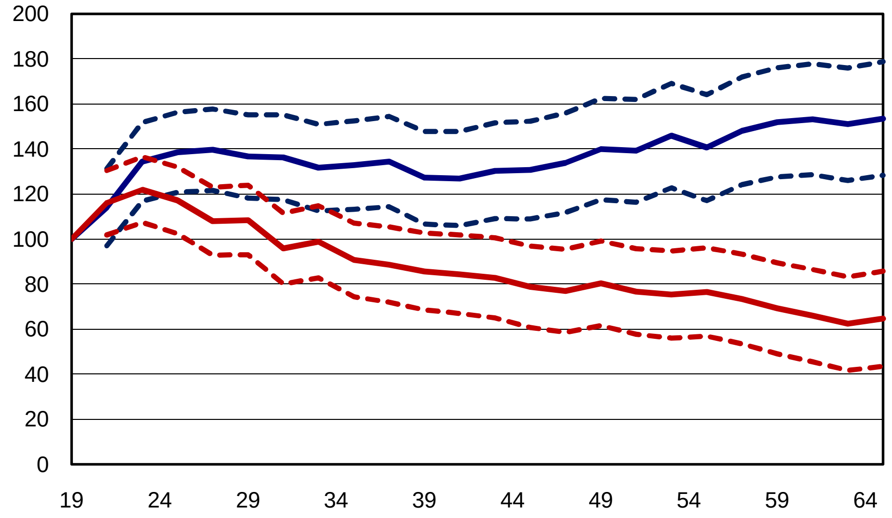
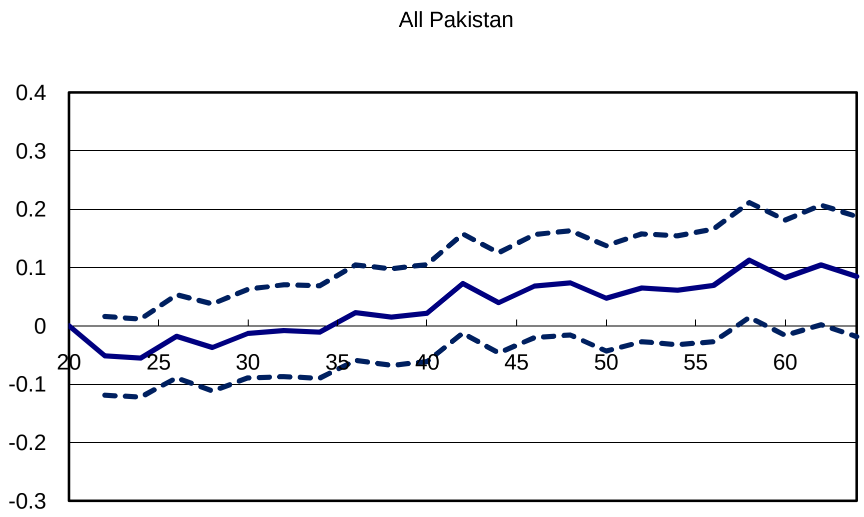
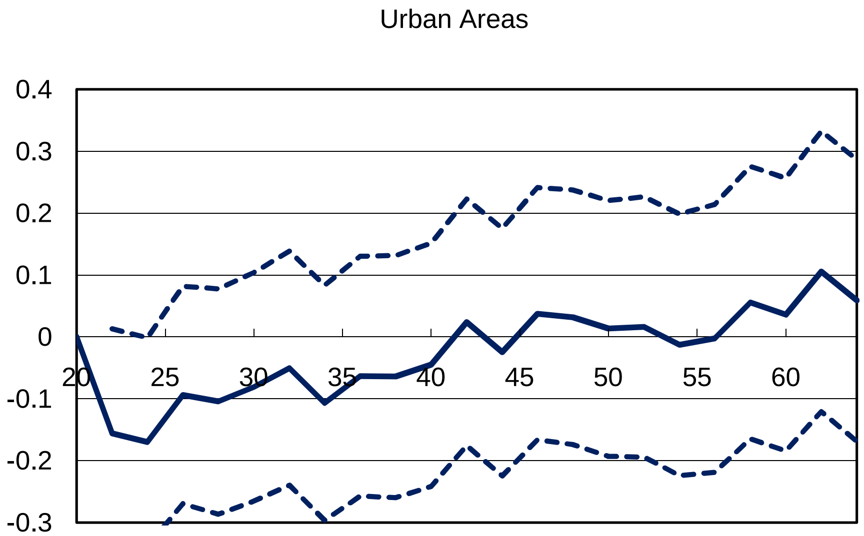


Figure 2-1.
Age effects in consumption inequality and regions, Pakistan

Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=20 as reference)
Source: Estimated from Pakistan's PIHS/PSLM data using weighted regression
to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 20 to 70.
Using 4 rounds from 1998/99 to 2005/06, age and cohort f.e. in 2-year intervals
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 56,238 for all Pakistan, 21,986 for urban areas, and 34,252 for rural areas.





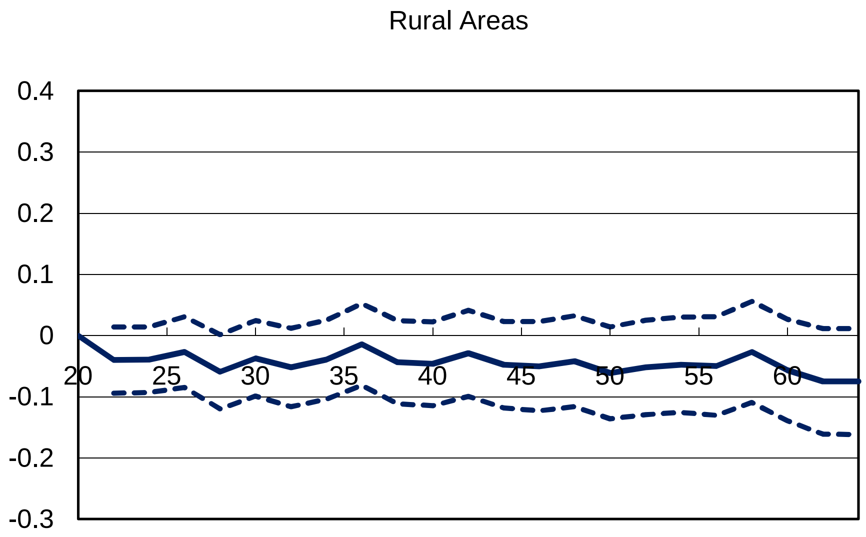
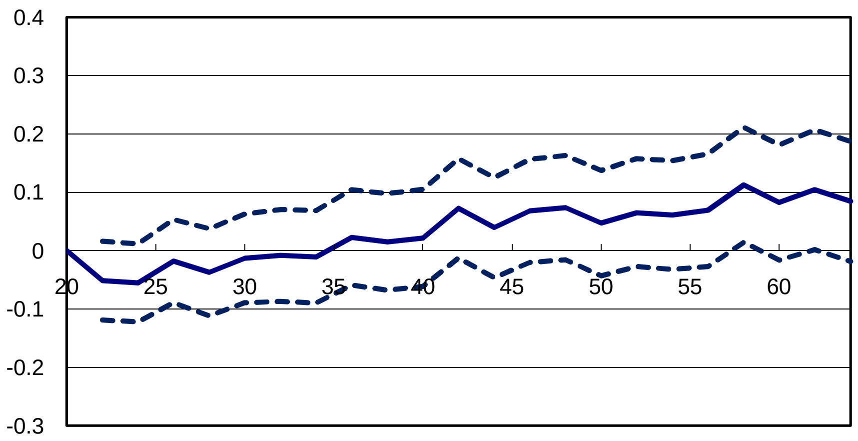


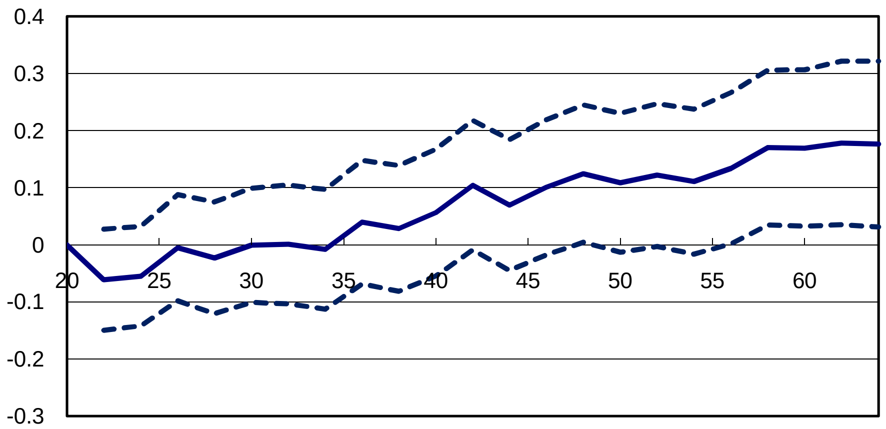
Figure 2-2.
Age effects in consumption inequality and education, Pakistan

Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=20 as reference)
Source: Estimated from Pakistan's PIHS/PSLM data using weighted regression
to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 20 to 70.
Using 4 rounds from 1998/99 to 2005/06, age and cohort f.e. in 2-year intervals
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 29,628 for the more educated hhs, 26,610 for the less educated hhs.

All Pakistan



Household head with higher education



Household head with lower education

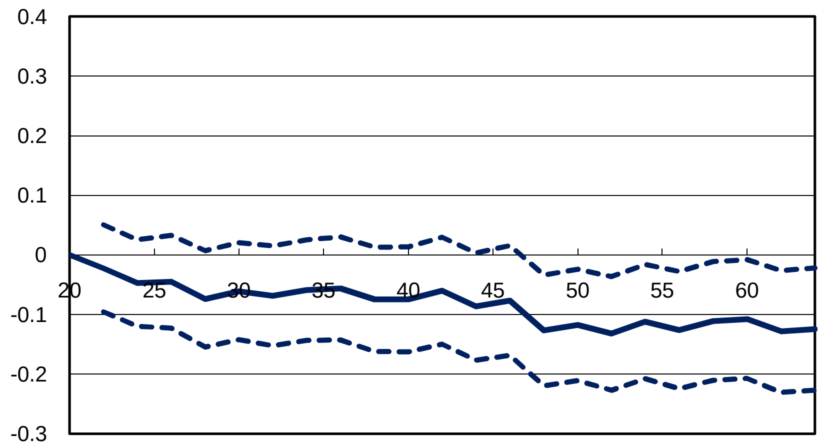
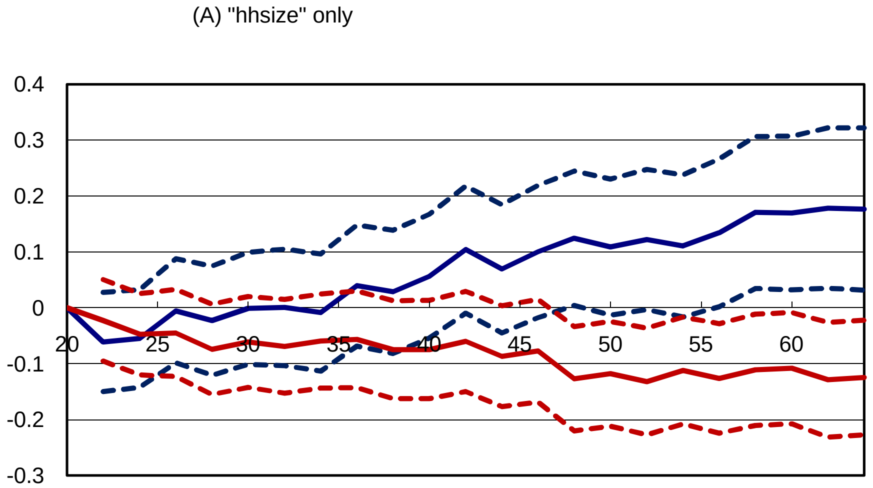


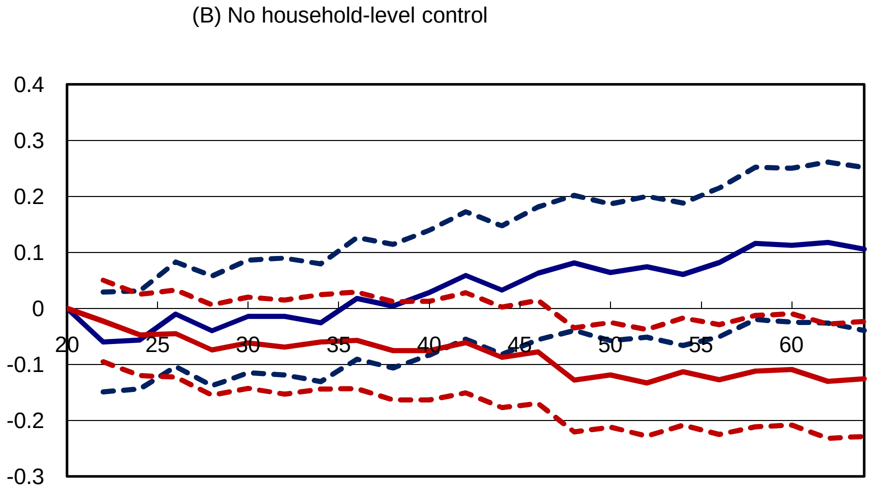
Figure 2-3.
Education contrast in age effects and household-level controls, Pakistan

Dashed lines show 95% confidence interval.
Violet: Household head with higher education
Red: Household head with lower education

Pooled regression with COHORT f.e. and AGE f.e. and other controls:

(A) "hhsize" only (same as Figure 2-2).
(B) No household-level control
(C) Full controls of demographic and regional controls such as demographic variables (dummy for female headed hh, dummy for head's absence, dummy for missing information on head's actual birth date, size of household in numbers, and size of household in adult equivalents) and regional fixed effects (province dummies, urban dummy)





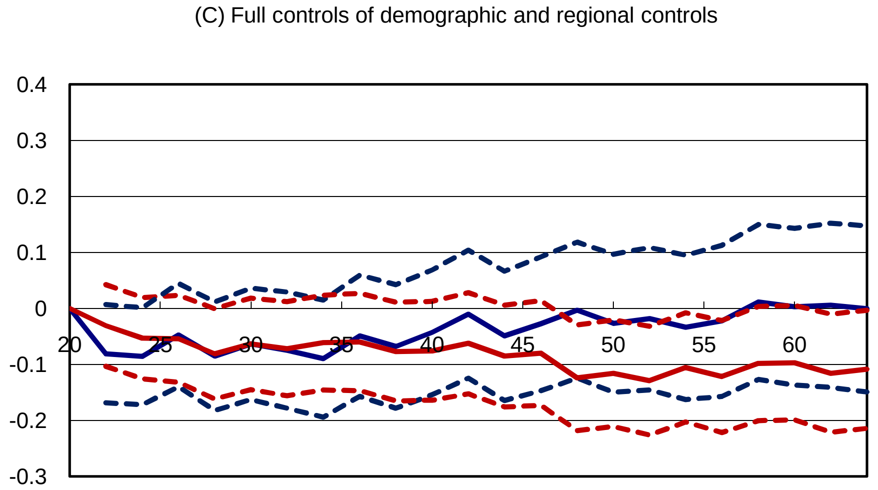
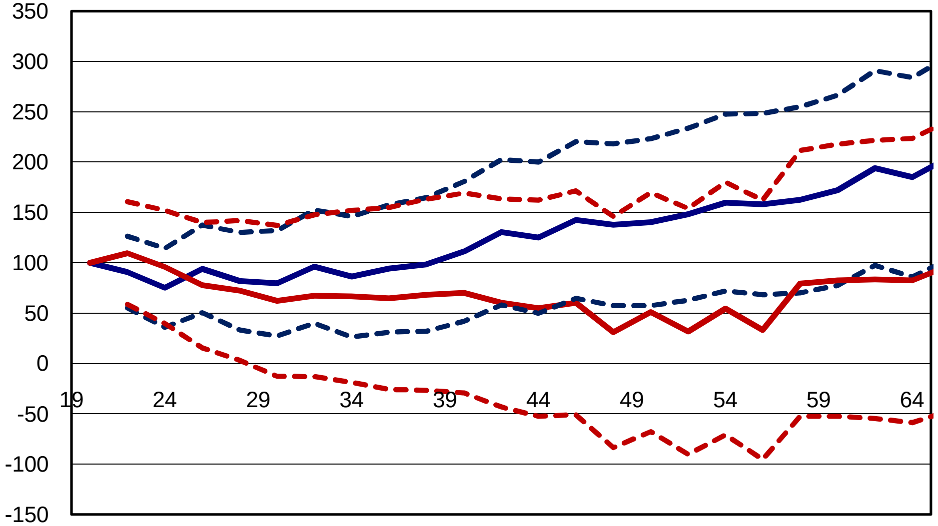


Figure 2-4. Education contrast in age effects in consumption inequality and inequality aversion parameter, Pakistan

(A) Atkinson inequality measure with parameter = 1

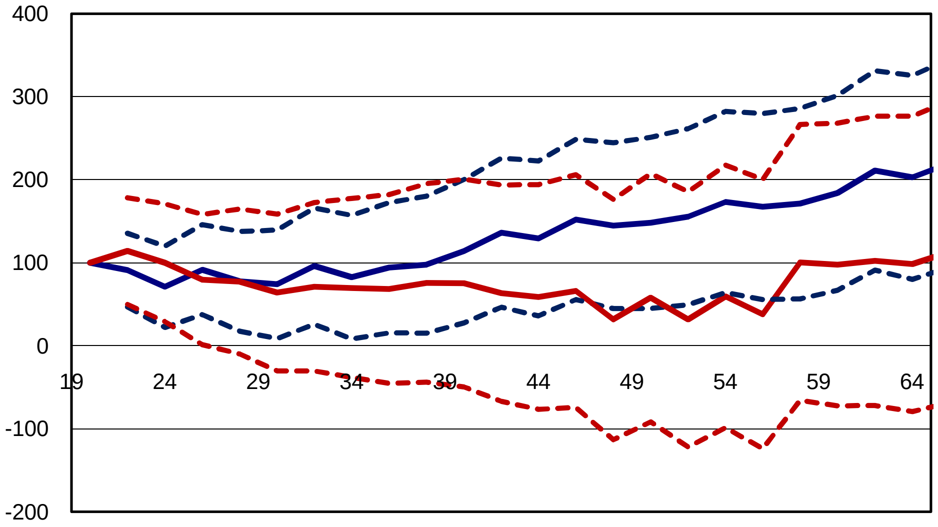


Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Index using the predicted value for Age=20 (reference) as 100
Source: Estimated from Pakistan's PIHS/PSLM data by OLS.
Cohort-level data, hh head's age in the range from 20 to 70.
Using 4 rounds from 1998/99 to 2005/06, age and cohort f.e. in 2-year intervals
NOB=104.

Violet: Household head with higher education
Red: Household head with lower education

Inequality aversion parameter for the Atkinson inequality measures is set at:
(A) Parameter = 1
(B) Parameter = 0.5 (less inequality-averse)
(C) Parameter = 2 (more inequality-averse)

(B) Parameter = 0.5 (less inequality-averse)



(C) Parameter = 2 (more inequality-averse)

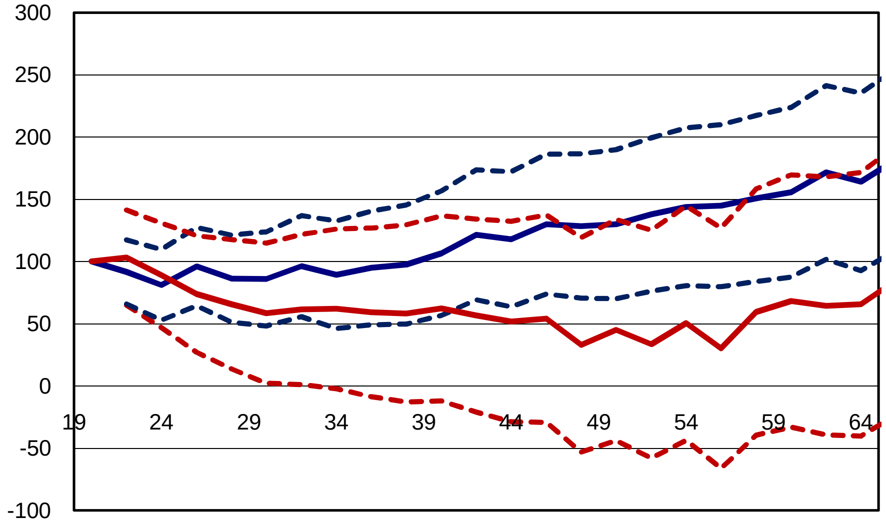
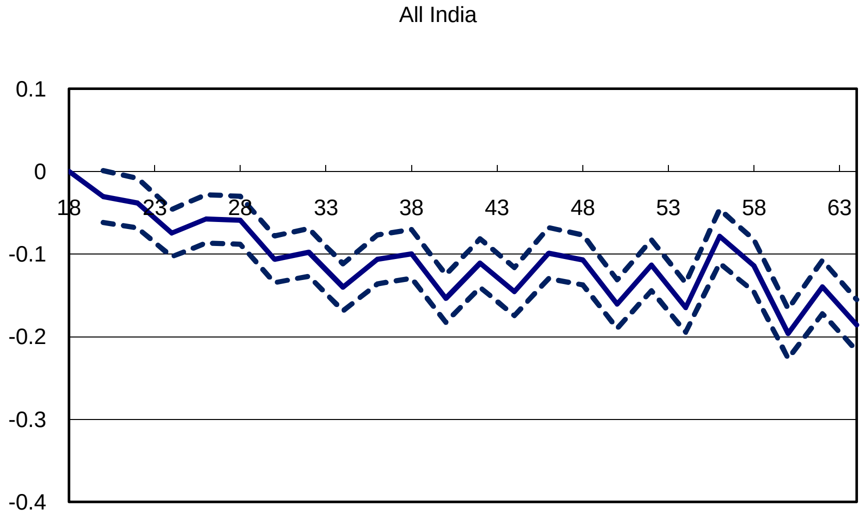
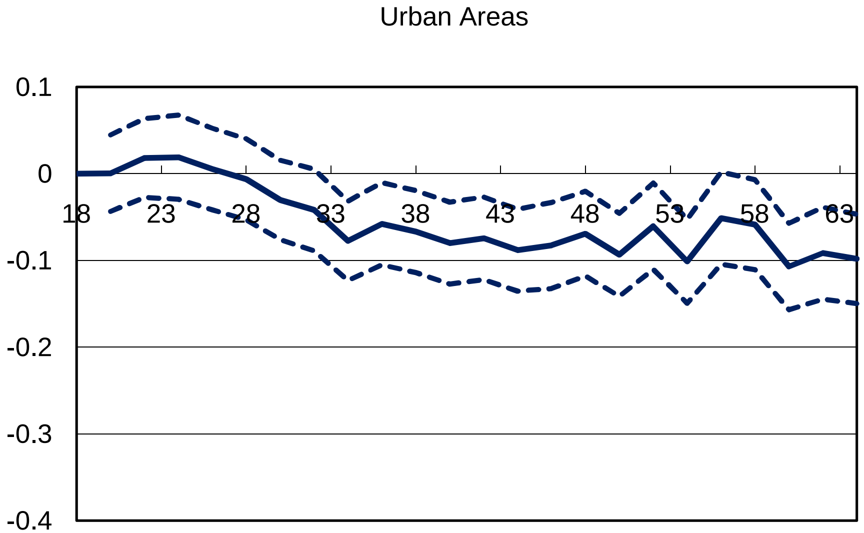


Figure 3-1.
Age effects in consumption inequality and regions, India

Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=18 as reference).
Source: Estimated from India's NSS data using weighted regression to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 18 to 70.
Use 4 rounds from 1983 to 2000, age in 2-year intervals and cohorts in 5-year intervals.
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 437,605 for all India, 162,026 for urban areas, and 275,579 for rural areas.





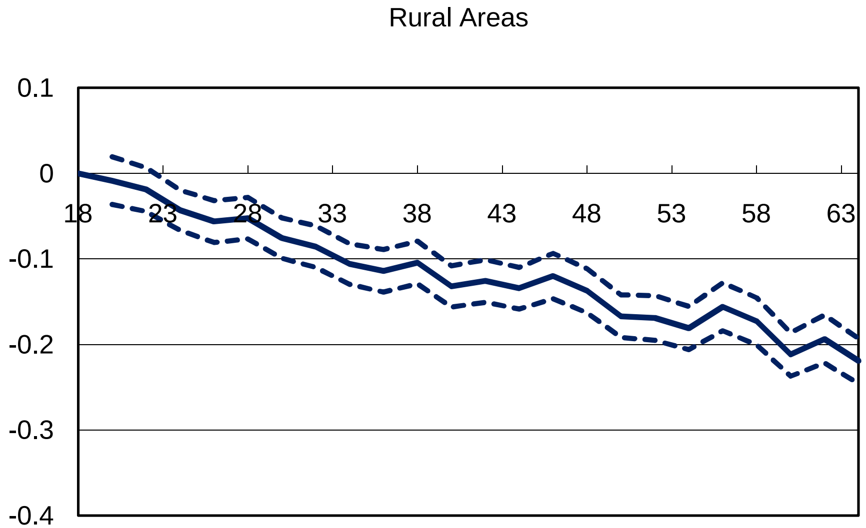
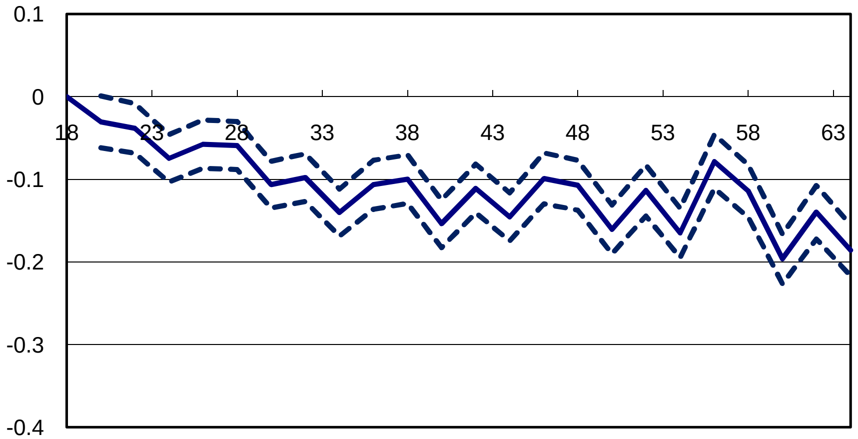


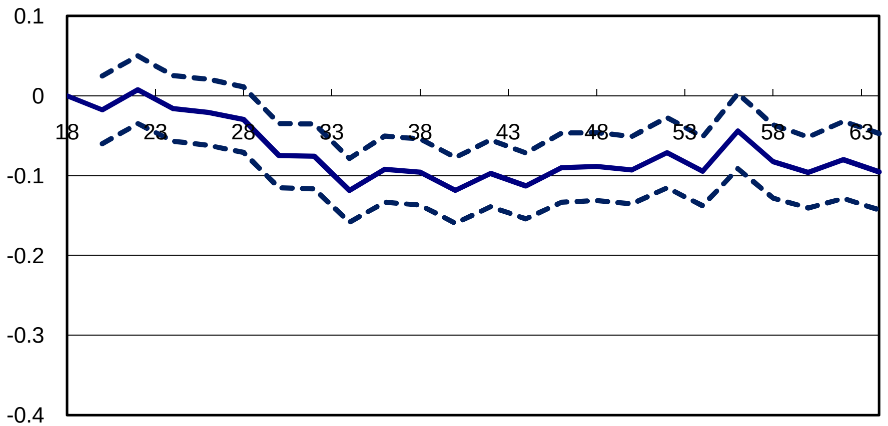
Figure 3-2.
Age effects in consumption inequality and education, India

Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Coeff. on AGE f.e. (Age=18 as reference)
Source: Estimated from India's NSS data using weighted regression
to control for the difference in sampling probability.
Individual-level data, hh head's age in the range from 18 to 70.
Use 4 rounds from 1983 to 2000, age in 2-year intervals and
cohorts in 5-year intervals.
Pooled regression with COHORT f.e. and AGE f.e.
Other controls: demographic variable (hhsize).
NOB: 199,477 for the more educated hhs,
238,128 for the less educated hhs.

All India



Household head with higher education



Household head with lower education

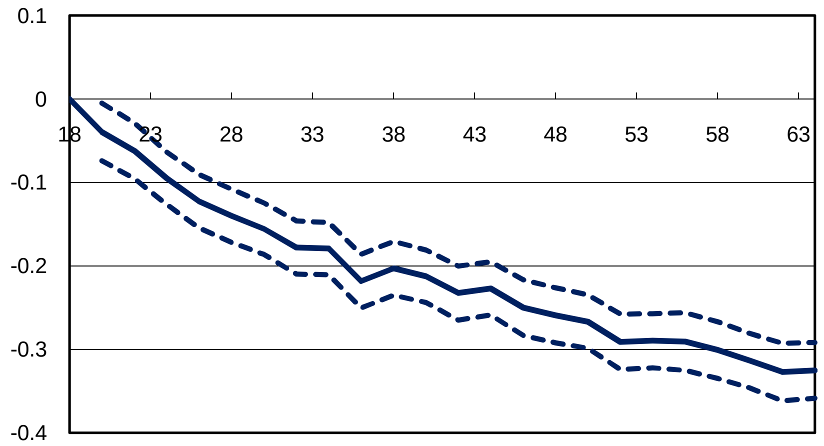
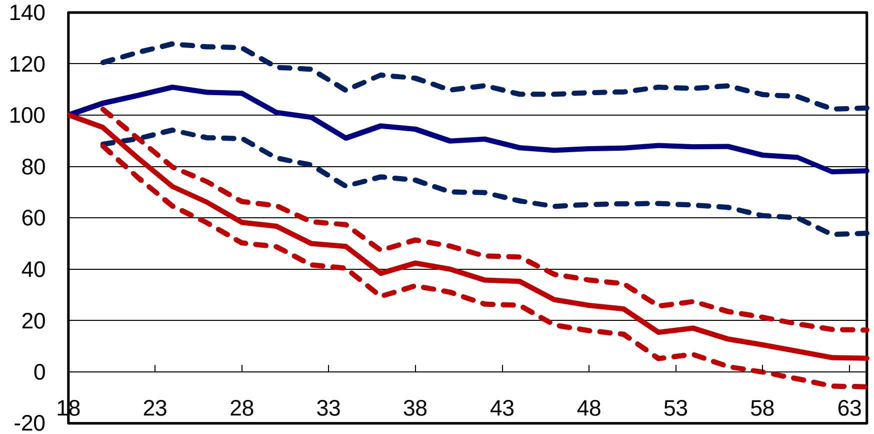


Figure 3-3. Education contrast in age effects in consumption inequality and inequality aversion parameter, India

(A) Parameter=1

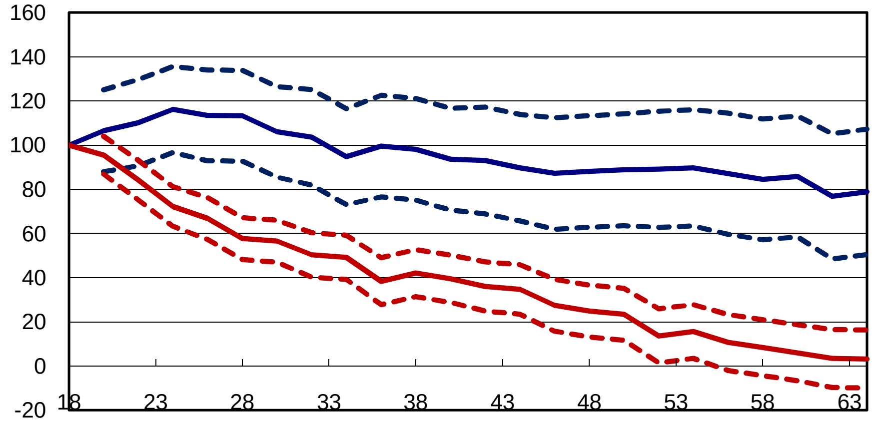


Dashed lines show 95% confidence interval.
Horizontal axis=age of the household head.
Vertical axis: Index using the predicted value for Age=18 (reference) as 100.
Source: Estimated from India's NSS data by OLS.
Cohort-level data, hh head's age in the range from 18 to 70.
Use 4 rounds from 1983 to 2000, age in 2-year intervals and
cohorts in 5-year intervals
NOB=108.

Violet: Household head with higher education
Red: Household head with lower education

Inequality aversion parameter for the Atkinson inequality measures is set at:
(A) Parameter = 1
(B) Parameter = 0.5 (less inequality-averse)
(C) Parameter = 2 (more inequality-averse)

(B) Parameter=0.5 (less inequality-averse)



(C) Parameter=2 (more inequality-averse)