IRLE WORKING PAPER
#117-05
February 2005

China's Income Distribution, 1985-2001

Ximing Wu and Jeffrey M. Perloff

China's Income Distribution, 1985-2001

Ximing Wu
University of California, Berkeley

Jeffrey M. Perloff
University of California, Berkeley

China's Income Distribution, 1985-2001

Abstract

We employ a new method to estimate China's income distributions using publicly available interval summary statistics. We examine rural, urban and overall income distributions from 1985-2001. We show how the distributions change directly as well as examine trends in equality. Using an inter-temporal decomposition of aggregate inequality, we determine that increases in inequality within rural and urban sectors and the growing rural-urban income gap have been equally responsible for the growth in overall inequality over the last two decades. However, the rural-urban gap has played an increasingly important role in recent years. We also show that urban consumption inequality rose considerably.

China's Income Distribution, 1985-2001

Ximing Wu* and Jeffrey M. Perloff**

February, 2005

We are very grateful to Peter Lanjouw, Shaohua Chen, and James Galbraith for extremely helpful comments, and Youjuan Wang, director of the household survey division of the Urban Survey Organization at the National Bureau of Statistics of China, for explaining many features of the Chinese urban survey. Ximing Wu acknowledges financial support from Social Science and Humanities Research Council of Canada.

* Department of Economics, University of Guelph, Guelph, Ontario, Canada, N1G 2W1.
Tel: (519) 824-4120, ext. 53014; xiwu@uoguelph.ca.

** Department of Agricultural and Resource Economics, University of California, Berkeley, 207 Giannini Hall, Berkeley, CA, 94720-3110; member of the Giannini Foundation.
Tel: (510) 642-9574; perloff@are.berkeley.edu.

Abstract

We employ a new method to estimate China's income distributions using publicly available interval summary statistics. We examine rural, urban, and overall income distributions from 1985-2001. We show how the distributions change directly as well as examine trends in inequality. Using an inter-temporal decomposition of aggregate inequality, we determine that increases in inequality within rural and urban sectors and the growing rural-urban income gap have been equally responsible for the growth in overall inequality over the last two decades. However, the rural-urban gap has played an increasingly important role in recent years. We also show that urban consumption inequality rose considerably.

JEL Code: O15, O18, O53

I. Introduction

Using a new technique to estimate income distributions from grouped summary statistics, we show that Chinese income inequality rose substantially from 1985 to 2001 because of increases in inequality within urban and rural areas and the widening rural-urban income gap. We find that China's dramatic economic growth—a five-fold increase in the economy and a four-fold increase in per capita income since the early 1980s—has disproportionately favored the urban areas and the rich. We also show that the rural and urban income distributions have evolved along separate paths, and this divergence has contributed markedly to the rise in the overall level of inequality.

Although a few articles have reported that income inequality in China increased rapidly over the last two decades, none shows by exactly how much inequality rose because of the absence of consistent, reliable income distribution estimates over time. The Chinese government provides Gini indices for only a few, random years using unspecified data sources, income definitions, and methodologies, hence its inequality measures may not be directly comparable over time (Bramall, 2001). Moreover, the Gini index only reflects some aspects of the underlying income distribution: A large amount of information is lost. Two Lorenz curves with the same Gini value may have different shapes. Thus, welfare implication from comparing Gini coefficients (or other summary statistics) may be ambiguous. Consequently, we report several summary statistics as well as reliable estimates of the entire income distribution.

This paper makes four contributions. First, we use the new method introduced in Wu and Perloff (2003) to estimate flexible income distribution functions when summary statistics are only available by intervals rather than for the entire distribution. Using the income summary statistics based on China's annual national household survey, we estimate rural, urban and overall income distributions for each year from 1985 through 2001. Based on these estimated income distributions, we provide the first intertemporally-comparable series of income inequality estimates of China based on a single consistent data source, methodology, and set of definitions.

Second, we show how the rural, urban, and overall Chinese income distributions evolved over time, and not merely how an arbitrarily chosen summary statistic, such as the Gini, changed. We show that the rural and urban income distributions evolved along different paths. We employ a simple new measure of the overlap between two distributions, which is the area under both density functions: the intersection.

Third, we decompose China's total inequality between rural and urban sectors to explore the distributional impacts of income growth, rural-urban income gap, and urbanization over time. We show that the rising inequality within both rural and urban areas, the widened rural-urban income gap, and the shift of populations between these two areas were responsible for the rise in aggregate inequality. We show that the widening rural-urban income gap played a major role in China. For our sample period, urbanization affects the inequality within either sector and between two sectors significantly, but these effects are offsetting.

Fourth, we examine the consumption inequality for urban areas. Consumption inequality is an alternative indicator for economic well-being. We find that the consumption inequality is also rising rapidly in China.

Section 2 discusses possible causes for the increase in China's overall inequality. The following section describes the available data. The fourth section presents our method to estimate maximum entropy densities using grouped data. The fifth section estimates China's income distributions and inequality for 1985-2001. The sixth section shows the relationship between total inequality and rural and urban inequality. The seventh section presents measures of consumption inequality for urban areas. The last section summarizes our results and presents conclusions.

II. Causes of Increased Inequality

The existing literature (Khan and Riskin 1998, Gustafsson and Li 1999, Yang 1999, Li 2000, and Meng 2003) argues that income inequality has increased markedly in China over the last couple of years. Khan and Riskin (1998) and Li (2000) also provide evidence that China's rural and urban income inequality differ and are growing at different rates.

We will present evidence that the increase in China's overall inequality is due to increases in *within inequality*, the inequality within the rural sector and within the urban sector, and *between inequality*, the inequality due to differences in the average income level between the rural and urban sectors. Our explanation is a generalization of two popular explanations—the Kuznets curve hypothesis and the structural hypothesis—which have contrasting implications about future inequality.

Kuznets (1953) stressed the role of between inequality in explaining the evolution of total inequality over time. He hypothesized that, if between inequality is greater than within inequality in each sector, then overall inequality will initially rise as people move from the low-income (rural) sector to the high-income (urban) sector. Later, inequality will fall, as most of the population settles in the high-income, urban sector. The resulting inverted U-shape relationship between inequality and the income level is called a Kuznets curve. If this hypothesis is true, the increase in inequality in developing countries during the course of urbanization may be a transitory process, and inequality will decline at the conclusion of the urbanization process.

Chang (2002) argues that "… a cure for this problem is to accelerate urbanization in the short run and to promote the growth of the urban sector in the long run. Yet, these policies in the short run may further widen the measured income gap." However, the urban sector may not be able to absorb the large rural surplus workers (150 million according to Chang, 2002). Therefore it is likely that China will maintain a high level of income inequality for an extended period.

A similar explanation starts from the same premise that the rural-urban income gap is the driving force for increased overall inequality, but holds that the adjustments described by Kuznets will not occur due to the secular demographic and institutional structure of China. According to this explanation, China's population has been divided into separate rural and urban economies. To a limited degree, migrants from rural areas may seek jobs in urban areas but China's strict residence registration system usually prevents them from obtaining urban residence status (and hence access to welfare benefits and subsidies enjoyed by urban residents and higher paying jobs). For example, Yang (1999) uses a static "within and between" analysis of household survey data from two provinces for 1986, 1992, and 1994 to argue that increases in rural–urban income differentials is the major cause of rising overall aggregate inequality in China.[1] He suggests that urban-biased policies and institutions are responsible for the long-term rural–urban divide and the recent increase in disparity. If barriers to migration remain, then inequality is unlikely to diminish in the future.

Thus, both of these hypotheses emphasize the rural-urban gap as the primary cause of increasing aggregate inequality. This factor is certainly part of the explanation for growing inequality. However, the complete story is more complex. We will present evidence that, over the last two decades, the increase in both within and between inequality contributed substantially to increased aggregate inequality. In particular, we show that if one takes into account urbanization, changes in within and between inequality were equally responsible for the increase in overall inequality (in contrast to the traditional static analysis which concludes that between inequality was largely responsible).

III. Data

We rely on the largest, most representative survey of Chinese households. The National Statistics Bureau of China (NSB—formerly SSB) conducts large-scale annual household surveys in rural and urban areas. The surveys cover all 30 provinces. They usually include 30,000 to 40,000 households in urban areas and 60,000 to 70,000 in rural areas. The NSB uses a two-tier stratified sampling scheme to draw a representative random sample of the population. Each household remains in the survey for three consecutive years, and keeps a record of their income and expenditure.

Because we do not have access to the underlying individual data from the NSB survey for all regions and all years, we estimate the Chinese rural and urban income distributions using publicly available summary statistics. Unfortunately, the NSB does not provide summary statistics for the entire sample, but only for various income intervals. These interval summary statistics are published for urban and rural areas in the *Chinese Statistics Yearbook* ("Yearbook" henceforth). The Yearbook defines the family income as annual per capita family disposable income. Our sample covers 1985 through 2001, a period for which the Yearbooks provide consistent data over time.

The Yearbooks summarize the income distributions differently for rural and urban areas. Rural income distribution is divided into a fixed number of intervals. The limits for these income intervals and the share of families within each interval are reported, as is the average income of the entire distribution, but not the conditional mean of each interval. The Yearbooks report 12 rural income intervals for 1985–1994, 11 for 1996, and 20 for 1995 and 1997–2001. For urban areas, the Yearbooks report the conditional mean of the 0-5th, 5-10th, 10-20th, 20-40th, 40-60th, 60-80th, 80-90th, and 90-100th percentiles of the income distribution, but not the limits of these income intervals. We use these publicly available grouped data to estimate the underlying distributions and draw inequality inferences from estimated income distributions. Both rural and urban income are deflated by the corresponding Consumer Price Index (CPI) from the Yearbook.

IV. Maximum Entropy Density Estimation with Grouped Data

Many earlier studies (e.g., Gastwirth and Glauberman 1976, Kakwani and Podder 1976, and Chen et al. 1991) estimated inequality and poverty using grouped data. These papers concentrated on estimating the Lorenz curve and its associated inequality indices. In contrast we use the method developed in Wu and Perloff (2003) that generalizes the traditional maximum entropy density method to estimate a very general income density function using grouped data. By so doing, in addition to determining the Lorenz curve and various welfare indices, we can examine the shape of the entire income distribution and how it changes over time.

The principle of maximum entropy (Jaynes, 1957) is a general method to assign values to probability distributions on the basis of partial information. This principle states that one should choose the probability distribution, consistent with given constraints, that maximizes Shannon's entropy. Traditionally, this maximum entropy density can be obtained by maximizing Shannon's information entropy

$$W = -\int p(x) \log p(x)\, dx$$

subject to K known moment conditions for the entire range of the distribution

$$\int p(x)\, dx = 1,$$
$$\int g_i(x)\, p(x)\, dx = \mu_i, \quad i = 1, 2, \ldots, K.$$

We can solve this optimization problem using Lagrange's method, which leads to a unique global maximum entropy (Zellner and Highfield, 1988 and Wu, 2003). The solution takes the form

$$p(x) = \exp\left(-\lambda_0 - \sum_{i=1}^{K} \lambda_i g_i(x)\right),$$

where λ_i is the Lagrange multiplier for the i^{th} moment constraint. This maximum entropy method is equivalent to a maximum likelihood approach where the likelihood function is defined over the exponential distribution and therefore consistent and efficient. See Golan and Judge (1996) for a discussion of how these two approaches are dual.

All the best-known distributions can be described as maximum entropy densities subject to simple moment constraints, which we will call "characterizing moments" henceforth. These characterizing moments are sufficient statistics for exponential families; the entire distribution can be summarized by the characterizing moments.

When only grouped summary statistics are reported, we can estimate the maximum entropy density by incorporating the grouped information as partial moments. Suppose that, for a certain distribution, we only know the grouped summary statistics of M intervals, with interval limits $[l_0, l_1, \ldots, l_M]$, and J conditional moments of each interval

$$\begin{bmatrix} \nu_{1,1} & \nu_{2,1} & \cdots & \nu_{M,1} \\ \nu_{1,2} & \nu_{2,2} & \cdots & \nu_{M,2} \\ \vdots & \vdots & \ddots & \vdots \\ \nu_{1,J} & \nu_{2,J} & \cdots & \nu_{M,J} \end{bmatrix} \tag{1}$$

where $\nu_{m,1}$ is the share of the m^{th} interval, and $\sum_{m=1}^{M} \nu_{m,1} = 1$. We define the j^{th} partial moment of a distribution $p(x)$ over the m^{th} interval as

$$\nu_{m,j} = \int_{l_{m-1}}^{l_m} f_j(x)\, p(x)\, dx,\ m = 1,\dots, M \text{ and } j = 1,\dots, J.$$

Given the underlying density function is $p(x) = \exp\left(-\lambda_0 - \sum_{i=1}^{K} \lambda_i g_i(x)\right)$, we calculate $p(x)$ using the partial moment conditions.[2] Substituting $p(x)$ into the partial moment conditions, we obtain a system of ($M \times J$) equations, one for each entry of matrix (1). We can solve for the Lagrange multipliers by iteratively updating

$$\lambda^{(1)} = \lambda^{(0)} + \left(\mathbf{G}'\mathbf{G}\right)^{-1}\mathbf{G}'\mathbf{b},$$

with $b_{m,j} = \nu_{m,j} - \int_{l_{m-1}}^{l_m} f_j(x)\, p(x)\, dx$. The ($M \times J$) by J matrix **G** consists of M submatrices $\mathbf{G}^{(m)}$ ($J \times J$) stacked on top of one another, where

$$G_{ij}^{(m)} = \int_{l_{m-1}}^{l_m} g_j(x)\, g_k(x)\, p(x)\, dx,\ 1 \le i, j \le J.$$

When the interval limits are unknown, the estimation procedure is more complicated because we do not know over which ranges the conditional means should be evaluated. For example in the Yearbooks, unlike rural areas, only the share and conditional mean of each urban income interval are reported. The moment constraints take the form

$$\begin{aligned} \nu_{m,1} &= \int_{l_{m-1}(\ )}^{l_m(\ )} p(x)\, dx,\ m = 1,\dots, M, \\ \nu_{m,2} &= \int_{l_{m-1}(\ )}^{l_m(\ )} xp(x)\, dx, m = 1,\dots, M, \end{aligned} \qquad (2)$$

where the interval limits $l_m(\ )$s are functions of the unknown density function, $p(x)$. More details on this method are contained in Wu and Perloff (2003), in which we show how to estimate the location of these limits jointly with the density function using a Quasi-Newton's method.

Our new method enables us to estimate the entire distribution. We can then calculate any feature of the distribution of interest. This approach has two additional advantages. First, it allows one to estimate the distribution even when the interval limits for the grouping are unknown. Second, traditional methods consider only population share and conditional mean of each interval. In contrast, the new method can easily incorporate other forms of information, such as the variance or the Gini index of each interval, as partial moments. Therefore, although this maximum entropy method is designed for situation when information is scarce, it is able to accommodate information input of various forms.

Because we do not have individual Chinese data corresponding to the reported grouped information, we cannot directly examine the effectiveness of the proposed method using Chinese data. Nonetheless, we demonstrate the effectiveness of the proposed method using raw income data from the 2000 U.S. Current Population Survey (CPS) March Supplement: See the Appendix and Wu and Perloff (2003). Using the sequential updating method of model selection described in Wu and Perloff (2003), we find that the specification $p(x) = \exp\left(-\sum_{i=0}^{4} \lambda_i \log(1+x)^i\right)$ gives the best overall fit according to the bootstrapped Kullback-Leibler Information Criterion. This method works extremely well for the U.S. data: The fit is virtually as close as could be obtained with moment conditions for the entire sample. For example, given the population shares and means for 8 intervals but not the interval limits, the estimated distribution had a Gini of 0.413; whereas the Gini based on individual data is 0.414.

V. Rural and Urban Inequality over Time

Using this method, we estimate the Chinese rural and urban income distributions from publicly available summary statistics. In addition to using these estimated distributions to determine how the traditional inequality measures changed over time, we can compare the estimated distributions directly.

A. Traditional Measures of Inequality

We start by examining three traditional measures of inequality—the Gini Index, the mean logarithm deviation of income, and comparisons of quantile ranges—for rural and urban areas separately. We use these measures to examine how inequality has changed over time.

We estimate the rural income distribution subject to the proportion of families in each *known* interval. Because the limits for the income intervals are unknown for urban income, we estimate them jointly with the density function.[3] Again, we find that the specification $p(x) = \exp\left(-\sum_{i=0}^{4} \lambda_i \log(1+x)^i\right)$ gives the best overall fit for both areas according to the bootstrapped Kullback-Leibler Information Criterion.

Based on the estimated densities, we calculate various inequality measures. The first two columns of numbers in Table 1 contain the estimated Gini index for rural and urban areas for each year of the sample period. The next two columns show the rural and urban mean logarithm deviations ($MLD = 1/n\sum_i \log(\mu / x_i)$, where n is the number of people).[4]

According to both measures, rural areas have greater inequality than urban areas throughout the period. On average, the rural Gini is 1.4 times and the *MLD* is 2.2 times their urban counterparts.

The correlation between the Gini and the *MLD* is 0.76 for rural areas and 0.73 for urban areas. Both inequality measures for rural and urban areas increased steadily over the sample period. The rural Gini increased by 26% from 0.272 to 0.343. One reason we are confident that the Gini is capturing a real, upward trend is that we compared the calculated Lorenz curves from the estimated densities. For example, the 1985 Lorenz curves of rural and urban distributions lie above those for 2001 everywhere, suggesting that the 1985 distributions Lorenz dominate those for 2001.[5]

The rural *MLD*—which places a relatively large weight on the income at the low end of the distribution—increased by 67.7% from 0.127 to 0.213. Urban inequality rose faster, though it remained below that in rural areas. The urban Gini increased by 40.8% from 0.191 to 0.269, and the *MLD* nearly doubled from 0.060 to 0.119.

Another traditional approach to assess the changes in inequality is to compare quantile ranges. Because of the interval summary statistics nature of our data, the information loss for quantile estimates due to grouping may be less than that of inequality index of the entire range, which suffers from the aggregating over the top and bottom quantiles. The last four columns of Table 1 show the estimated 90/50 and 50/10 quantile ratios. If $Q(p)$ is the p^{th} percentile, then the 90/50 quantile ratio is $Q(90)/Q(50)$. The 90/50 ratio reflects the relative shares of a wealthy group to the average group. Similarly, the 50/10 quantile ratio shows the relative shares of the average to a poor group. For rural and urban areas, both measures increased by between 20 and 25% during the sample period. Although not shown in the table, the 90/10 ratio increased by around 50%. The similarity in changes of these quantile ratios suggests that the different inequality increase rate, as measured by Gini and *MLD*, is likely due to the difference in evolutions of the upper and lower tails of the distributions.

Given how China records rural migrants to urban areas, studies based on any Chinese data set measure rural and urban inequality differently than they would in other countries. As migrants from rural who work urban areas usually cannot obtain urban residence status, they are excluded from urban household surveys. Because most migrants can only obtain jobs that pay less than those of other urban workers and because the number of migrants grew considerably during the sample period, urban inequality measures are lower than if migrants were counted as urban residents.[6] On the other hand, if migrants earn relatively high incomes by rural standards, including them in the rural household surveys raises rural income inequality.[7] Moreover, Schultz (2003) notes that restrictions on permanent migration reduce the returns that rural youth can expect to realize through profitably moving to a higher wage labor market. Consequently, the household registration system increases the gap in investments in education between rural and urban families and the rural-urban gap in the long run.

B. Comparison with the Literature

We can compare our estimates to those from four previous studies. As these other studies only report the Gini for a few years, Table 2 compares the rural and urban Gini indexes for only those years.

Li (2000) reports rural and urban Gini index provided by the NSB for 1988 and 1995. Our estimates of the rural Gini of 0.300 in 1988 and 0.338 in 1995 are close to Li's (2000) estimates based on NSB data of 0.301 and 0.332. Our estimates of the urban Gini of 0.201 in 1988 and 0.221 in 1995 are not quite as close to Li's estimates, 0.23 and 0.28.

Because the NSB household survey data are not publicly available, the other three studies—Khan and Riskin (1998), Gustafsson and Li (1999), and Meng (2003)—use data from smaller, less representative surveys conducted by the Economics Institute of the Chinese Academy of Social Sciences (CASS) in 1988 and 1995.[8] The CASS uses a broader definition of income than does the NSB. Although three of these studies use the CASS data, their estimates of the Gini differ, because they make different assumptions about the underlying data (Bramall, 2001).

Khan and Riskin (1998) report higher rural inequality measures based on CASS data than either we or Li (2000) do based on NSB data. All three CASS studies estimate the 1988 urban Gini at 0.23 (above our estimate of 0.20), but their estimates of the 1995 value range from 0.28

to 0.33 (all higher than our 0.22). Thus, our urban estimates are lower than those of previous studies. The lower value of our estimates may be due to difference in the underlying data sources, definitions of income, or methodology.

Nonetheless, all studies report that rural and urban inequality increased from 1988 to 1995. In addition, Meng (2003) reports that the urban Gini increased from 0.282 in 1995 to 0.313 for 1999 based on a CASS survey covering six provinces.

The World Bank report, *Sharing Rising Incomes* (1997), estimated China's Gini index for 1981 through 1995. Both that report and we find (i) a drop in rural inequality in 1990; (ii) dips in urban inequality for 1989 through 1991 and 1995; and (iii) urban inequality lower than rural inequality throughout the period covered by both studies.

C. Examine Distributions Directly

Although they provide a straightforward way to examine the trend in inequality over time, the inequality indices only reflect certain aspects of the evolutionary process. For example, these summary statistics do not show how the general shape of the income distribution changed over time. Is the increased inequality as measured by the Gini or *MLD* caused by a rightward shift of the mode, a thickened tail, or some other more complex change? Does the distribution become bi-modal due to "hollowing out" of the middle class? For further insight into this process, we examine the shapes of our estimates of the flexible density function, which allows for multi-modal distributions.

Figure 1 shows how the rural distribution changed between 1985 and 2001, and Figure 2 shows the shift in the urban distribution. Throughout the sample period, each distribution has a single mode. However, dispersion increased considerably over time, largely because the right tails grew longer. Moreover, the income distributions gradually but persistently moved to the right (and correspondingly, the weight at the mode decreased), reflecting a general increase in incomes.

These rightward shifts in the distributions are more clearly seen by comparing distributions for pairs of years. The left panel of Figure 3 shows that the 2001 rural income distribution is much more dispersed than the 1985 distribution. The distribution mode rose 68% from 292 Yuan in 1985 to 490 (in 1985) Yuan in 2001. Despite the rightward shift of the mode, the skewness increased from 1.28 to 1.39. The height of the distribution at the mode in 2001 is only about 40% of the 1985 peak, which caused kurtosis to fall from 4.95 to 4.86.

The level and the dispersion of the urban income (right panel of Figure 3) rose more rapidly than in rural areas (left panel). Moreover, the fraction of households with very low levels of income fell substantially. The mode of the urban distribution increased by 140% from 681 Yuan in 1985 to 1,634 in (1985) Yuan in 2001, while the density of the mode in 2001 fell to 25% of that in 1985. The distribution became more symmetric—skewness decreased from 1.82 to 1.47—reflecting a relative decrease in the share of poor and increase in the share of wealthy people. The kurtosis fell from 8.28 to 6.05, reflecting the substantial flattening of the peak. Compared with the rural distribution, the share of people with low absolute income (the height of the left tail) was much smaller, which helps to explain why our inequality estimates are lower in urban areas, especially for the *MLD*, which heavily weights the income of the poor.

By how much did the distributions shift? We can assess the overall distance or closeness between two distributions directly. We propose a simple new measure of the overlap between two distributions, the intersection, which is the area under both density functions. This statistic for two density functions $p(x)$ and $q(x)$ on the real line or its subsets is defined as

$$\Omega = \int \min\left[p(x), q(x) \right] dx,$$

whose value is equal to area *B* in Figure 3.[9] It is restricted to lie within [0, 1]. If $\Omega = 0$, then $p(x)$ and $q(x)$ are disjoint. If $\Omega = 1$, then $p(x)$ and $q(x)$ coincide. We note that the size of area B is equal to one minus the two-sided Komogorov-Smirov statistics. Hence, test based on the overlapping area is asymptotically equivalent to the Komogorov-Smirov test.

Over our entire period, the density overlap, Ω, between each pair of adjacent years averages 0.944 and 0.922 for rural and urban area respectively. Comparing the distribution between 1985 and 2001, Ω is higher for rural areas, 0.544, than for urban areas, 0.236, reflecting the cumulative effect of larger change in urban income distribution during this period.

VI. Decomposition of Aggregate Inequality

What effect do these unequal shifts in the rural and urban distributions have on overall inequality? To answer this question, we decompose the total Chinese inequality between rural and urban areas. Our results suggest that increased inequality within either sector and between sectors contributed to the increase of total inequality.

A. Aggregate Distribution and Inequality

We compute China's aggregate income distribution as a population-weighted mixture of the rural and urban distributions. We use the resulting distribution to calculate the inequality indices of the aggregate distribution. Denoting rural and urban income distribution as $p_r(x)$ and $p_u(x)$ respectively, we obtain the aggregate distribution by taking their weighted sum:

$$p(x) = s_r p_r(x) + s_u p_u(x), \tag{3}$$

where s_r and s_u is the share of rural and urban population. During the sample period, the share of urban population increases steadily from 24% to 38%.

Figure 4 illustrates the relationship of the aggregate distribution (solid) to the rescaled rural (dot) and urban (dash-dot) distributions for 1985 and 2001. The rural and urban densities are rescaled by their corresponding population weights so that the areas below these two curves sum to one. By comparing the 1985 and 2001 figures, we see that the overall shape of the aggregate distribution was relatively unchanged over the sample period, but the right tail became thicker. The left tail of the 1981 aggregate density is almost completely coincident with the rural density (urban dwellers are not that poor) while both the rural and urban densities span the right tail. In 2001, the urban density is almost entirely responsible for the right tail of the aggregate density.

Table 3 reports the Gini index (second column) and the *MLD* (third column), which were calculated from the estimated aggregate $p(x)$. Over the sample period, the Gini index increased 34% from 0.310 to 0.415, and the *MLD* nearly doubled from 0.164 to 0.317. The overall inequality is much higher than either rural or urban inequality because of the substantial rural–urban income gap. As shown by Equation (3) and Figure 4, the increased aggregate inequality was due to changes in the rural or urban distributions, their interaction (the degree to which the two distributions overlap), and the population weights.

Although we have access to less information than was used in the 1997 World Bank report, both sets of estimates are very close. For example, our estimates of the overall Gini index of 0.310 in 1985 and 0.382 in 1995 (the first and last year of the period covered by both studies) are virtually identical to the World Bank's estimates of 0.31 for 1985 and 0.388 for 1995.

During our sample period, China's Gini index has averaged a 0.66 point increase each year, or a 2% annual growth. This dramatic increase is extremely unusual. Li et al. (1998) noted that income inequality has been relatively stable within countries (although it varies considerably among countries). They pointed to China as an exception because its Gini index grew 3% annually between 1980 and 1992. Starting with a modest inequality in the early 1980s, China now has the one of the highest inequality among developing countries. Indeed, China's current Gini inequality is at the same level as that of the United States, which has the highest Gini index among the OECD countries.

B. Decomposition of Aggregate Inequality

If an inequality index can be decomposed into within sector inequality and between sector inequality without an interaction term for the overlap of sectors, we can derive the aggregate inequality index from the indices for the subgroups of the population. The most commonly used inequality index, the Gini, is not decomposable in this sense, so generally we cannot calculate the aggregate Gini index from the Gini indices of its subgroups. However, the *MLD* is decomposable, so we can use the rural and urban *MLD*'s to derive the aggregate *MLD*, and we can show which factors contributed to the growth of the aggregate *MLD* over time.

The decomposition formula for the *MLD* index is

$$\begin{aligned} MLD &= \sum_k s_k MLD_k + \sum_k s_k \log\left(\frac{\mu}{\mu_k}\right) \\ &= MLD_W + MLD_b, \end{aligned} \tag{4}$$

where MLD_k is the inequality for the k^{th} subgroup (here, k = rural or urban), μ_k is the mean income of the k^{th} subgroup, and s_k is the population share of the k^{th} subgroup. The first term, MLD_w, is the *within inequality*: the inequality within the rural or urban sector. The second term, MLD_b, is the *between inequality*: the inequality due to differences in the average income level between rural and urban areas.[10]

Both within inequality and between inequality measures increased considerably during the sample period (last two columns of Table 3). Between inequality increased by more in both relative and absolute terms than within inequality. Between inequality increased by 163% from

0.053 to 0.139, while within inequality increased by only 61% from 0.111 to 0.178. As a result of both of these increases, total *MLD* inequality more than doubled.

To avoid year-to-year fluctuations, in Table 4, we show inequality increased over the entire period and in three subperiods: 1985 through 1990, 1990 through 1996, and 1996 through 2001. The first three columns of Table 4 report the average annual change in aggregate inequality for the entire period and three subperiods. During the sample period, the overall *MLD* inequality increased from 0.16 to 0.32. Although the average annual increase over the entire period was 0.01, the annual rate of increase rose over time, so that the average increase in the third subperiod was more than three times of that in the first two subperiods.

In the first subperiod, the contributions of changes in within (0.0026) and between (0.0019) inequality to the change in aggregate inequality are close. However, during the second and third subperiods, the between inequality's contribution increased relative to the within inequality. For the entire period, the increase in between inequality accounts for about 56% ($\approx$0.0054/0.0096) of the total increase.

Equation (4) shows that three factors contribute to total inequality: the inequality within each subgroup (MLD_k), the relative average income of each subgroup (μ_k/μ), and the population share of each subgroup (s_k). During the sample period, the share of rural population fell from 76% to 62%. However, the simple "within and between" analysis does not separate the impact of changes in population shares from that of changes in the distribution of each sector.

Following Mookherjee and Shorrocks (1982), we differentiate the static "within and between" decomposition to examine the effects of each component directly. Applying the difference operator to both sides of Equation (4), we obtain

$$
\begin{aligned}
\Delta MLD &= MLD_t - MLD_{t-1} \\
&= \Delta\left(\sum_k s_k MLD_k\right) + \Delta\left(\sum_k s_k \log\left(\frac{\mu}{\mu_k}\right)\right) \\
&\cong \sum_k \bar{s}_k \Delta MLD_k + \sum_k \Delta s_k \overline{MLD}_k + \sum_k \left(\bar{\eta}_k - \bar{s}_k\right)\Delta \log\left(\mu_k\right) + \sum_k \Delta s_k \left(\bar{\lambda}_k - \overline{\log\left(\lambda_k\right)}\right) \\
&= \underbrace{\theta_w + \theta_{sw}}_{\Delta MLD_w} + \underbrace{\theta_b + \theta_{sb}}_{\Delta MLD_b},
\end{aligned}
\tag{5}
$$

where $\lambda_k = \mu_k/\mu$, $\eta_k = s_k \lambda_k$, and a horizontal bar over a variable indicates that two periods are averaged. We further decompose the contribution from within inequality or between inequality into two components: a pure within or between effect and an effect caused by a change in shares of rural and urban populations. The last line of Equation (6) shows that the change in *MLD* is the sum of four effects: θ_w, the effect from changes in within inequality should the population shares remain constant; θ_{sw}, the effect of changes in population shares on within inequality; θ_b, the effect from changes in between inequality (the average income of each group) should the population shares remain constant; and θ_{sb}, the effect from changes in population shares on between inequality. Therefore, by explicitly accounting for the effects of changes in population shares, we are able to separate the contribution of each factor to the aggregate inequality.

We calculate the intertemporal decomposition for the entire period and three sub-periods. The last four columns of Table 4 report the *annual* change in each term in Equation (5) for the entire period and three sub-periods. The results suggest that the relative contribution of within inequality ignoring population shifts, θ_{w}, is larger than the static measure of the change of within inequality, $\Delta MLD_{\mathrm{w}} = \theta_{\mathrm{w}} + \theta_{\mathrm{sw}}$, which includes the effects of the changing population (θ_{sw}). That is, migration from higher-inequality rural areas to lower-inequality urban areas reduces the effect of rising within inequality. On average for the entire period, migration partially offsets the effect of increased within inequality by 16% (= 0.0008/0.0050).

In contrast, the contribution of between inequality—the rural-urban income gap—is smaller when we account for change in population shares. Because of the widening rural-urban income gap, migration enhances the effect of increased between inequality by 20% (= 0.09/0.45) on average.

The effects of migration on the within and between inequality are nearly offsetting (θ_{sw} + $\theta_{sb} \approx 0$). Overall, the static "within and between" decomposition underestimates the contribution of increased within inequality because it fails to take into account the influence of change in population shares. For the entire period, the change in within inequality accounts for 52% of the increase in total inequality, compared to 44% in the simple "within and between" decomposition.

The pattern varies over time. Initially within inequality played a larger role; but in recent years, between inequality contributed more to overall inequality change. After controlling for the effects of urbanization, we find that changes in within inequality were responsible for 67%, 39% and 53% of the change in total inequality for the three sub-periods respectively. It is in the late 1990s that the most dramatic increase in inequality occurs. The annual increase in aggregate inequality is 0.0202 in the *MLD*, compared with 0.0045 and 0.049 for the first two sub-periods.

VII. Consumption Inequality

Because we have been relying on highly aggregate income information, we consider an alternative approach in which we examine Chinese inequality in consumption, which may be a better indicator of economic well-being than income inequality. Consumption data are only available for urban areas, where consumption information is summarized in the same format as is income distribution by the Yearbooks.

Jorgenson (1998) argues that estimates of welfare indices depend critically on the choice between income and consumption as a measure of household resource. Permanent income may be the preferred indicator of household resource, but it is unobservable. Although measured income is correlated with permanent income, its substantial transitory component is uncorrelated with permanent income. Measured consumption can serve as a proxy for household permanent income, if it is proportional to permanent income. Moreover, it exhibits relatively smaller transitory fluctuation. Therefore, we may be able to make more reliable welfare inferences using consumption rather than income.

According to several studies of inequalities in the OECD countries, the recent rise in income inequality was not accompanied by a similar increase in consumption inequality. These findings are sometimes cited in response to public concern about rising income inequality. Regardless of the validity of this argument in OECD countries, it does not apply to China, where the income and consumption inequality measures are highly correlated. Figure 5 compares the estimated Gini index for income and consumption in the left panel and their growth rate in the right panel. Although consumption inequality is lower than income inequality, its growth rate closely parallels that of the income inequality.

A closer examination of the data reveals that prior to 1997, the ratio of average expenditure to average income for households within the 0-5th percentiles of the income distribution averaged 1.06. Hence, consumption by households with very low income exceeded their income, probably due to dissavings or government subsidies for urban residents. However, the consumption–income ratio for the bottom five percentiles fell to 0.96 for 1997–2001, suggesting that households at the lower end of the income distribution might not be able to smooth consumption against low income.

VIII. Summary

We examine the evolution of China's income distribution and inequality from 1985 through 2001. We estimate China's income distribution using a new maximum entropy density approach that works well when only a limited set of summary statistics by income interval are available. The maximum entropy principle is a general method to assign values to probability distributions on the basis of partial information. We extend this method to grouped data and use it on summary statistics of income data from annual Chinese household surveys. We are able to confirm that this new method works extremely well on U.S. data.

Using this new technique and data from the most inclusive Chinese survey, we are able to provide the first inter-temporally comparable estimates of China's inequality measures. In contrast, most previous studies of Chinese income inequality used an alternative survey that is only available in a couple of years and that does not cover the entire country.

We find that rural and urban inequality have increased substantially. Urban inequality was lower than rural inequality during the sample period, but it is rising faster. Direct examination of the estimated distributions reveals that both rural and urban income distributions are shifting to the right over time. The overall dispersion increased considerably, due in large part to the growth of the right tail of the distribution and the failure of the share of the very poor to decline significantly.

Rising inequality within rural and urban areas, the widening rural-urban income gap, and shifts of population between urban and rural areas combined to drive up the aggregate inequality substantially. In contrast to previous studies that used static decompositions that attributed the growth in overall inequality largely to increases in the rural-urban gap, our dynamic decomposition shows that the increase in within and between inequality contributed equally to the rise in overall inequality over the last two decades. However, we find that the rural-income gap has played an increasingly important role in recent years.

Finally, we observe that consumption inequality, arguably a better indicator of economic well-being than income inequality, has also risen substantially during the sample period. Thus, we are even more convinced that inequality is rising rapidly in China.

In short, Chinese rural, urban, and overall income inequality are high (compared to developing countries and most developed countries) and rising due to increases in within and between inequality. Currently rural incomes are less equally distributed than urban incomes. However, urban inequality is increasing faster than rural inequality. At its current rate, urban inequality will eventually overtake rural inequality. Moreover, this trend would further accelerate the increase in inequality as people move to urban areas. On the other hand, the Chinese government restricts free migration from rural to urban areas. Even if such migration were permitted, it probably is not possible for the urban economy to accommodate the majority of the gigantic rural population. Thus, in contrast to the prediction of the Kuznets curve, where the majority of the population end up in the urban sector, gaps between rural and urban incomes may persist and cause overall inequality to rise for an extended period.

REFERENCES

Bramall, C., "The Quality of China's Household Income Surveys," *The China Quarterly* 167 (2001), 689-705.

Chang, G. H., "The Cause and Cure of China's Widening Income Inequality," *China Economic Review* 13 (2002), 335-40.

Chen, S., M. Ravallion, and G. Datt, "POVCAL -- a Program for Calculating Poverty Measures from Grouped Data," Memo, World Bank (1991).

Gastwirth, J., and M. Glauberman, "The Interpolation of the Lorenz Curve and Gini Index from Grouped Data," *Econometrica* 44:3 (1976), 479-83.

Golan, A., G. Judge, and D. Miller, *Maximum Entropy Econometrics: Robust Estimation with Limited Data* (New York: John Wiley and Sons, 1996).

Gustafsson, B., and S. Li, "A More Unequal China? Aspects of Inequality in the Distribution of Equivalent Income," Unpublished Manuscript (1999).

Jaynes, E. T., "Information Theory and Statistical Mechanics," *Physics Review* 106 (1957), 620-30.

Jorgenson, D., "Did We Lose the War on Poverty?" *Journal of Economic Perspectives* 12:1 (1998), 79-96.

Kakwani, N. C., and N. Podder, "Efficient Estimation of the Lorenz Curve and Associated Inequality Measures from Grouped Observations," *Econometrica* 44:1 (1976), 137-48.

Khan, A. R., and C. Riskin, "Income Inequality in China: Composition, Distribution and Growth of Household Income, 1988 to 1995," *The China Quarterly* 154 (1998), 221-53.

Kuznets, S., *Shares of Upper Income Groups in Income and Savings* (New York: National Bureau of Economic Research, 1953).

Li, H., L. Squire, and H. Zou, "Explaining International and Intertemporal Variations in Income Inequality," *The Economic Journal* 108 (1998), 26-43.

Li, S., "Changes in Income Inequality in China Transition," Mimeo, Chinese Academy of Social Sciences (2000).

Meng, X., "Economic Restructing and Income Inequality in Urban China," Research Paper, Australian National University (2003).

Mookherjee, D., and A. Shorrocks, "A Decomposition Analysis of the Trend in U.K. Income Inequality," *Economic Journal* 92:368 (1982), 886-902.

Schultz, T. P., "Human Resources in China: The Birth Quota, Returns to Schooling, and Migration," Working Paper, Yale University (2003).

The World Bank, *Sharing Rising Incomes*, World Bank Report (1997).

Wu, X., "Calculation of Maximum Entropy Densities with Application to Income Distribution," *Journal of Econometrics* 115 (2003), 347-54.

Wu, X., and J. M. Perloff, "Maximum Entropy Density Estimation with Grouped Data," Working Paper (2003).

Yang, D. T., "Urban-Biased Policies and Rising Income Inequality in China," *American Economic Review Papers and Proceedings* 89:2 (1999), 306-10.

Zellner, A., and R. A. Highfield, "Calculation of Maximum Entropy Distribution and Approximation of Marginal Posterior Distributions," *Journal of Econometrics* 37 (1988), 195-209.

Appendix: Numerical Example of Maximum Entropy Distributions for Grouped Data

We demonstrate the effectiveness of the proposed method using raw income data from the 2000 U.S. Current Population Survey (CPS) March Supplement. The March CPS, a large annual demographic file with 35,297 observations, includes labor market and income information for the previous year, so the data pertain to tax year 1999.

Corresponding to the different ways the income distributions are summarized in the *Chinese Statistical Yearbook*, we run three experiments. To be consistent with the China data, we divide the U.S. income into 12 and 20 intervals respectively. We then estimate the maximum entropy densities $p_1(x)$ based on 12 intervals and $p_2(x)$ based on 20 intervals, using the corresponding interval limits and share of families in each interval. In the third experiment, we calculate the conditional mean of the 0-5th, 5-10th, 10-20th, 20-40th, 40-60th, 60-80th, 80-90th, and 90-100th percentiles of the income distribution. We then estimate the maximum entropy density, $p_3(x)$, subject to the share and conditional mean of each interval, but do not use the interval limits. We find that the specification $p\left(x\right)=\exp\left(-\sum_{i=0}^{4}\lambda_i \log\left(1+x\right)^i\right)$ produces the best fit according to the bootstrapped Kullback-Leibler Information Criterion. We compare the estimated densities using two standard measures of inequality, the Gini index and the mean logarithm deviation (*MLD*). The Gini index and *MLD* from both the raw data and the estimated densities are reported in Table A1. The estimates from the fitted densities are close to those obtained from the full sample.

Table A1. Estimated inequality indices

	Full sample	P_1	p_2	p_3
Gini	0.414	0.409	0.418	0.413
MLD	0.338	0.335	0.348	0.333

In the third experiment, because the limits for the income intervals are unknown, we estimate them jointly with the parameters of the density. The results (in tens of thousands of dollars) are reported in Table A2. They are close to the corresponding sample quantiles.

Table A2. Estimated quantiles

Quantile	*5th*	*10th*	*20th*	*40th*	*60th*	*80th*	*90th*
Sample	0.097	0.146	0.226	0.386	0.580	0.865	1.154
Estimated	0.092	0.147	0.232	0.384	0.566	0.879	1.226

We can also compare the estimated densities directly using graphs. Figure A1 plots the estimated densities against the histogram of the full sample. Our estimated maximum entropy densities successfully capture the shape of the empirical distribution.

Table 1. Estimated Inequality Indices for Rural and Urban Areas

	Gini		*MLD*		*50/10 Ratio*		*90/50 Ratio*	
Year	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*	*Rural*	*Urban*
1985	0.272	0.191	0.126	0.060	1.887	1.478	1.900	1.529
1986	0.284	0.189	0.141	0.059	2.011	1.493	1.956	1.515
1987	0.279	0.194	0.135	0.062	1.976	1.488	1.945	1.533
1988	0.300	0.201	0.160	0.064	2.088	1.524	2.004	1.564
1989	0.305	0.198	0.165	0.063	2.113	1.530	2.064	1.572
1990	0.288	0.198	0.145	0.064	2.012	1.533	1.991	1.569
1991	0.315	0.184	0.178	0.054	2.16	1.483	2.08	1.527
1992	0.317	0.200	0.178	0.065	2.128	1.553	2.126	1.58
1993	0.319	0.219	0.178	0.077	2.123	1.605	2.196	1.682
1994	0.300	0.229	0.156	0.085	2.08	1.661	2.123	1.721
1995	0.338	0.221	0.206	0.079	2.301	1.629	2.205	1.683
1996	0.316	0.221	0.154	0.079	2.123	1.629	2.055	1.690
1997	0.322	0.232	0.168	0.087	2.087	1.682	2.105	1.728
1998	0.321	0.239	0.184	0.093	2.219	1.715	2.147	1.755
1999	0.325	0.246	0.188	0.099	2.227	1.746	2.164	1.790
2000	0.339	0.258	0.210	0.109	2.373	1.791	2.245	1.843
2001	0.343	0.269	0.213	0.119	2.367	1.839	2.301	1.887

Table 2. Comparison of Gini Coefficients

		Gini			
		Rural		*Urban*	
Source	*Data Set*	1988	1995	1988	1995
This study	NSB	0.300	0.338	0.201	0.221
Li (2000)	NSB	0.301	0.323	0.23	0.28
Khan and Riskin (1998)	CASS	0.338	0.416	0.233	0.332
Gustafsson and Li (1999)	CASS			0.228	0.276
Meng (2003)	CASS			0.234	0.282

Table 3. Total Inequality and Its Decomposition

Year	*Gini*	*MLD*		
		total	*within*	*between*
1985	0.310	0.164	0.111	0.053
1986	0.311	0.169	0.121	0.048
1987	0.317	0.175	0.117	0.058
1988	0.337	0.201	0.135	0.066
1989	0.342	0.208	0.138	0.070
1990	0.327	0.186	0.124	0.062
1991	0.345	0.215	0.144	0.070
1992	0.361	0.231	0.147	0.084
1993	0.380	0.255	0.150	0.105
1994	0.381	0.252	0.136	0.116
1995	0.382	0.266	0.169	0.096
1996	0.349	0.215	0.131	0.084
1997	0.375	0.258	0.143	0.116
1998	0.378	0.257	0.154	0.103
1999	0.389	0.272	0.157	0.115
2000	0.407	0.305	0.174	0.131
2001	0.415	0.317	0.178	0.139

Table 4. Contribution of each factor to change in total inequality

Year	Δ *MLD*	ΔMLD_w	ΔMLD_b	θ_w	θ_{sw}	θ_b	θ_{sb}
1985—1990	0.45	0.26	0.19	0.30	-0.04	0.13	0.06
1990—1996	0.49	0.12	0.36	0.19	-0.07	0.28	0.09
1996—2001	2.02	0.93	1.09	1.06	-0.13	0.96	0.11
1986—2001	0.96	0.42	0.54	0.50	-0.08	0.45	0.09

Note: All numbers have been multiplied by 100.

[1] Because Yang's analysis is restricted to only two provinces for a shorter time period, his results are not directly comparable to our results.

[2] In general, the functional form $p(x)$ is unknown. Wu and Perloff (2003) discuss choosing a model using bootstrapped Kullback-Leibler Information Criterion.

[3] We have more confidence in our rural income distribution estimate than our urban one because the rural distribution is summarized in more intervals (20 versus 8), spans the entire distribution relatively evenly, and has income limits. More importantly, the top urban interval covers the entire 90-100th decile. If most of the increase in dispersion at the high end of the distribution occurred within the top decile during our sample period, we cannot recover this increase in inequality without further information.

[4] The *MLD* belongs to the generalized entropy family, $I_a = \sum_i \left[(x_i/\mu)^a - 1\right]/[na(a-1)]$, where $a \geq 0$. A low value of a indicates a high degree of "inequality aversion". One can show that $\lim_{a \to 0} I_a = \frac{1}{n}\sum_i \log\left(\mu / x_i\right)$, which is the *MLD*. In this study, we focus on the *MLD* as it gives the simplest formula for the intertemporal decomposition of inequality (see Section 5).

[5] Given the estimated density f and sample average μ, the Lorenz curve is obtained numerically as $L(p) = 1/\mu \int_0^{F^{-1}(p)} xf(x)\,dx$, where F^{-1} is the inverted distribution function.

[6] During the sample period, the share of the rural population fell from 76% to 62%. The number of migrant workers is estimated to be around 80 million in the mid-1990s. See Bramall (2001) and references therein.

[7] According to Youjuan Wang, director of the household survey division of the Urban Survey Organization at the National Bureau of Statistics of China, migrants are not included in the urban

sample and their income is only reflected in the rural sample if they remit income to family members remaining in rural areas. However, if the entire family migrates, they would not be included in either the urban or rural household survey during our sample period. China's new survey design will include migrants in the urban sample.

[8] Unlike the NSB survey that covers all 30 provinces, the CASS survey covered 28 provinces for rural areas and 19 provinces for urban areas in 1988, and 10 provinces for rural areas and 11 provinces for urban areas in 1995.

[9] Compared with another commonly used distance measure such as the Kullback-Leibler distance, $\int p(x)\ln\left[p(x)/q(x)\right]dx$, our measure has three advantages. First, it has an intuitive graphic interpretation as the overlapping areas of two distributions. Second, and more important, it is symmetric in the sense that Ω is invariant to the order of $p(x)$ and $q(x)$: $\Omega_{p,q} = \Omega_{q,p}$. Third, this index can be used to compare directly more than two distributions.

[10] For example, suppose $x_1 = [1, 2]$ and $x_2 = [3, 4, 5]$. Using the formula, $MLD = \frac{1}{n}\sum_i \log\left(\mu / x_i\right)$, we calculate $MLD_1 = 0.5[\log(1.5/1) + \log(1.5/2)] = 0.06$ and similarly $MLD_2 = 0.02$. Using Equation (4), $MLD_w = 0.4MLD_1 + 0.6MLD_2 = 0.04$. We can calculate $MLD_b = \text{MLD}(1.5, 1.5, 4, 4, 4) = 0.1$ because, if we give every member of a group its group average, then the inequality of the entire population is the between inequality. Finally, $MLD_w + MLD_b = 0.14 = MLD(1, 2, 3, 4, 5)$.

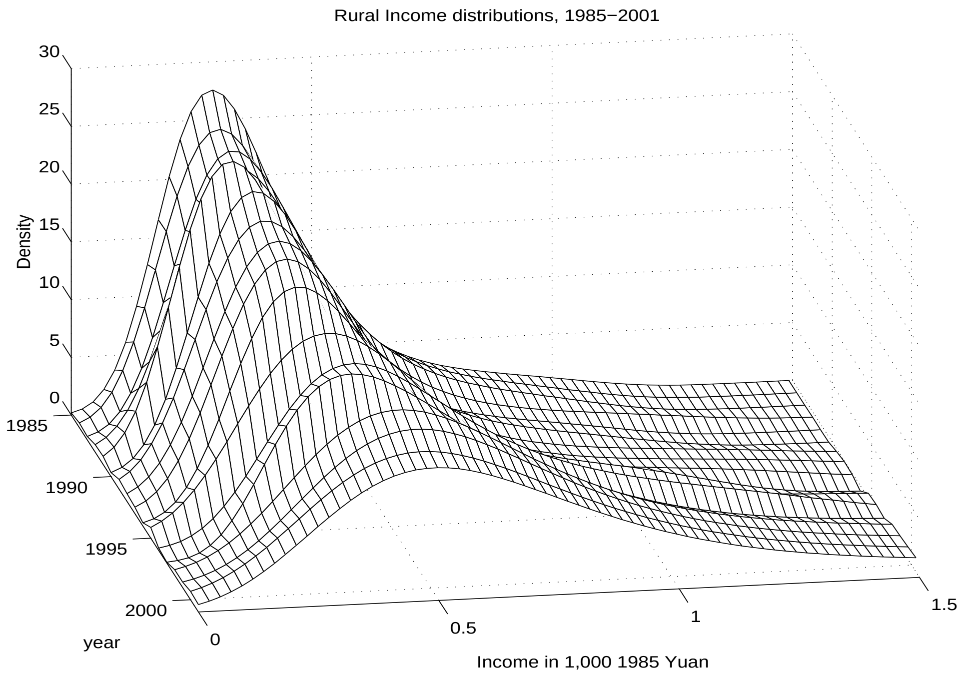

Figure 1: Rural income distributions, 1985–2001

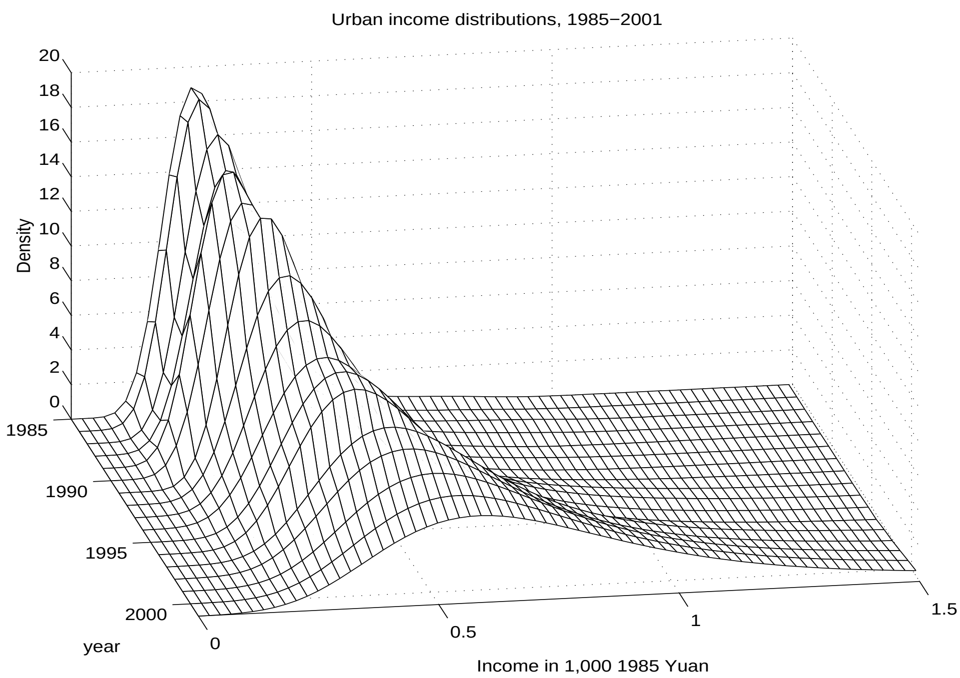

Figure 2: Urban income distributions, 1985–2001

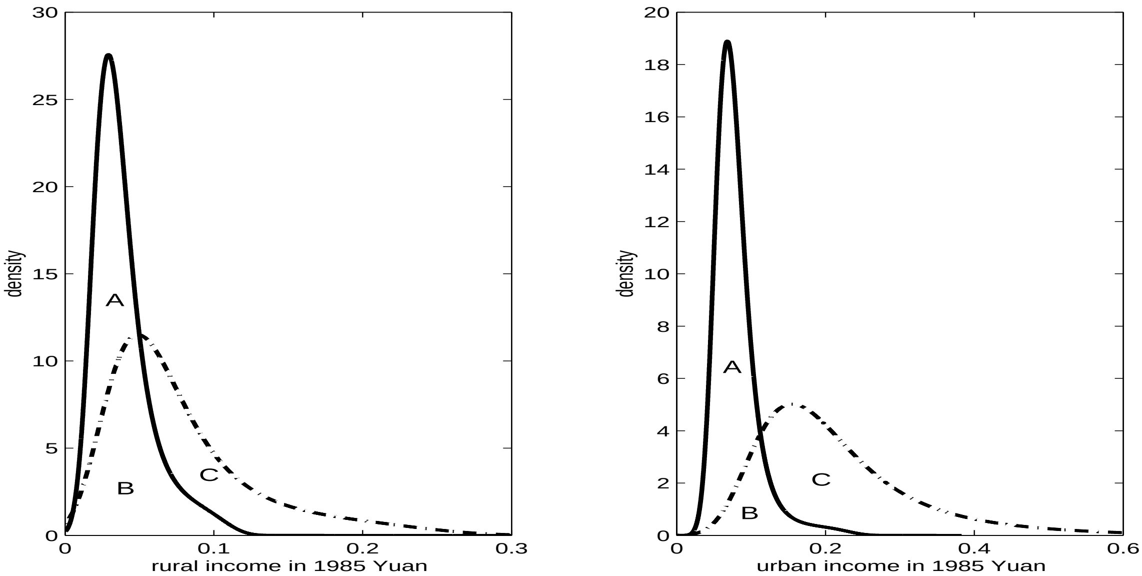

Figure 3: Estimated rural and urban distributions in 1,000 1985 Yuan. (1985: solid; 2001: dashes and dots)

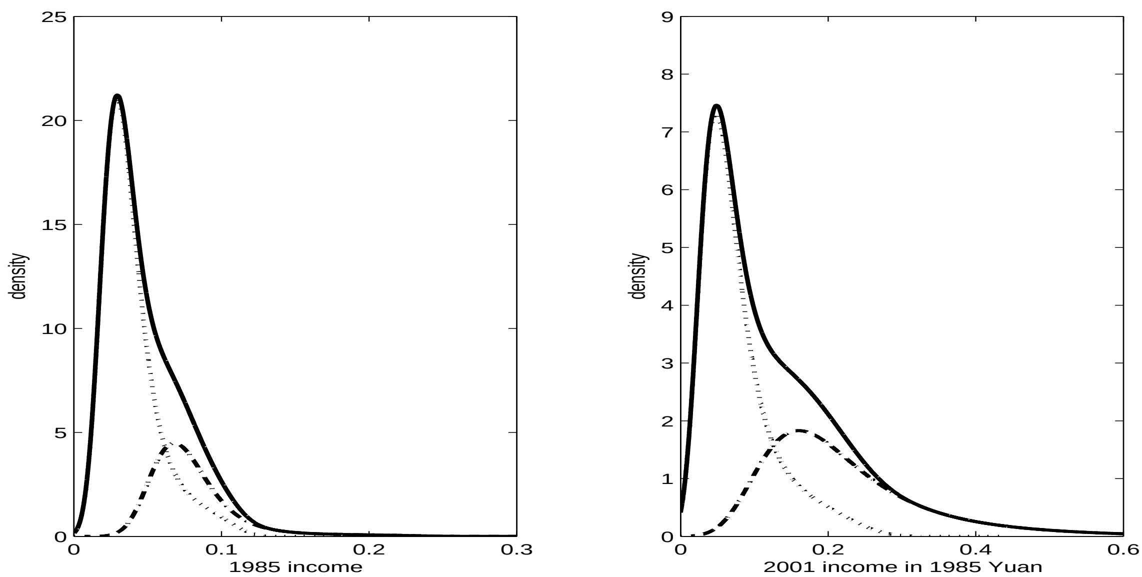

Figure 4: Rural (dots), urban (dashes) and aggregate (solid) distributions in 1,000 1985 Yuan

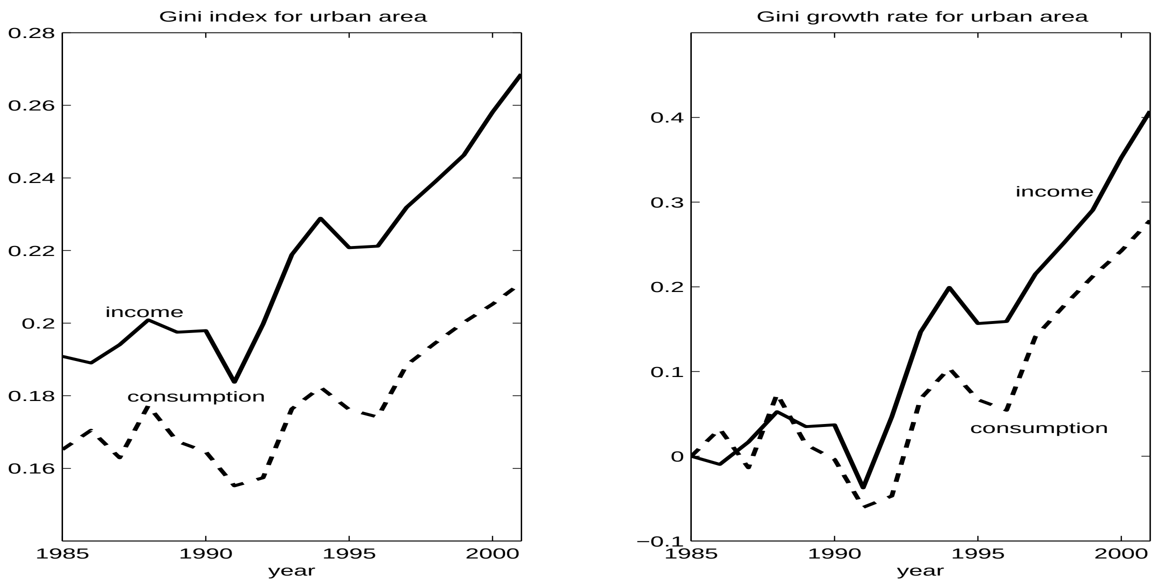

Figure 5: Gini index and growth rate for urban areas, 1985-2001 (income: solid; consumption: dashes)

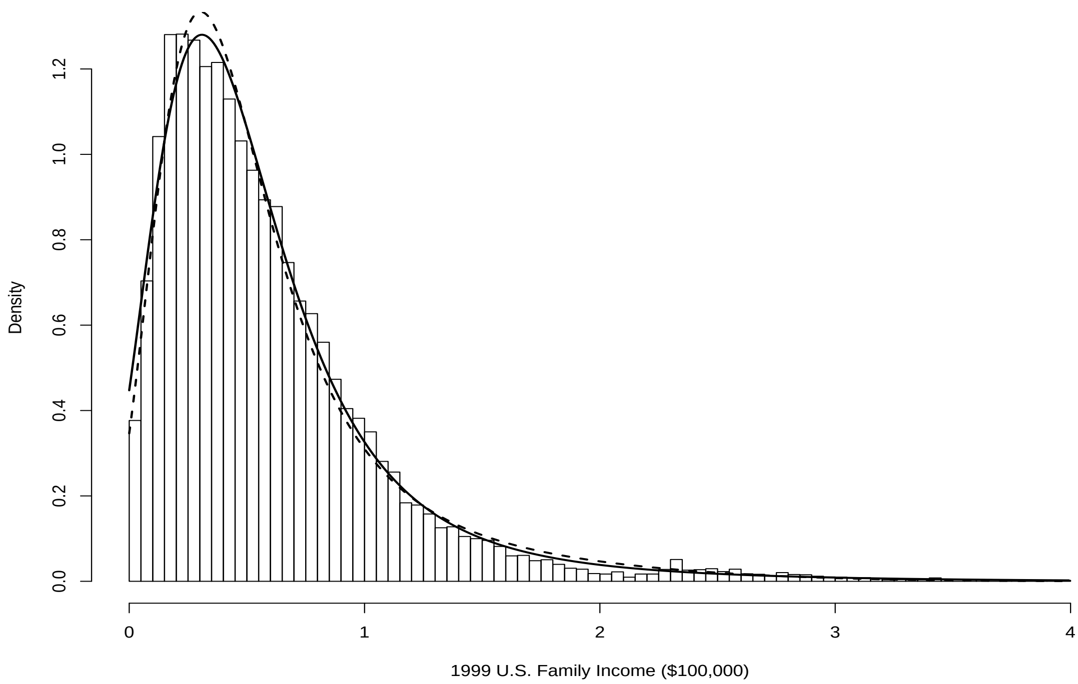

Figure A1: Estimated maximum entropy densities (p_2: solid; p_3: dashes; p_1, which is nearly perfectly identical to p_2, is not shown)