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Why Do Poverty Rates Differ From Region to Region?

The Case of Urban China

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Abstract

This paper proposes a semi-parametric method for poverty decomposition, which combines the data-generating procedure of Shorrocks and Wan (2004) with the Shapley value framework of Shorrocks (1999). Compared with the popular method of Datt and Ravallion (1992), our method is more robust to misspecification errors, does not require the predetermination of functional forms, provides better fit to the underlying Lorenz curve and incorporates the residual term in a rigorous way. The method is applied to decomposing variations of urban poverty across the Chinese provinces into three components – contributions by the differences in average nominal income, inequality and poverty line. The results foreground average income as the key determinant of poverty incidence, but also attach importance to the influence of distribution. The regional pattern of the decomposition suggests provincial groupings based not entirely on geographical locations.

Keywords: poverty, Shapley decomposition, China

JEL classification: O15, O53

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The Tables and the Figure appear at the end of this paper.

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1 Introduction

Across nations and regions the incidence of income poverty varies. After controlling for local standards of living, the variations are attributable to differences in the size of the economic pie (relative to the size of the population) – characterized by the average income, and to differences in how the pie is divided – captured by the Lorenz curve or income inequality. Quantifying the relative role of the two factors in determining the spatial variations of poverty provides valuable insights for the design and execution of poverty alleviation policies. In particular, it helps to answer the heavily disputed question: which is more important for the poor, growth or redistribution?

Previous efforts to decompose the variations of poverty incidence over time and across space have been hampered by two issues. The first is that household survey data are not readily accessible at the household/individual level. The published data are mostly grouped in the format of either range-frequency distribution or quantiles. The parametric approach to recovering the Lorenz curve from grouped data requires specifying a functional form for the Lorenz curve or the size distribution of income. This practice inevitably involves the risk of misspecification. This is not helped by the fact that while many such functions have been proposed, none has emerged as dominantly superior in empirical applications. The second issue relates to the intricate way that average income and inequality affect poverty. The marginal impact on poverty of one factor is not independent of the level of the other. The normal practice of changing one while holding the other constant results in an awkward residual term which, as earlier studies (e.g., Datt and Ravallion 1992) show, can be quite significant.

This paper suggests a decomposition method combining the recent progress on both fronts. First, it employs a method devised by Shorrocks and Wan (2004) to generate individual income data from just a few Lorenz coordinates. This enables us to estimate poverty measures with limited information without recourse to parameterized Lorenz curves or income distributions. Second, it adopts the Shapley value decomposition procedure proposed by Shorrocks (1999) to produce exact decomposition, thereby avoiding the unexplainable residual term. The method is then applied to analysing the variations of urban poverty across the Chinese provinces.

The spatial variation of urban poverty in China is of interest in its own right. The unbalanced growth and economic reform have enlarged the differences in development levels among the Chinese provinces. In 1998, the average urban resident in Shanghai earned more than twice as much as one in Shanxi. The incidence of urban poverty varies by a much larger magnitude, ranging from 0.68 to 13.5 per cent according to Hussain (2003). Interestingly, the variations do not coincide with the spatial pattern of average income, with some of the more affluent provinces recording higher poverty rates than the poorer ones. As mentioned earlier, the spatial differences in mean income can only account for part of the spatial variation in poverty. It would be useful to explore how much of the variation is due to disparities in average income and whether the relative contribution of income gaps differs significantly across provinces. Answers to these questions have important implications for the formulation of poverty reduction policies aimed at helping the lagging provinces.

Earlier research on poverty in China has basically focused on rural poverty. There have been several attempts at assessing the scale of urban poverty and decomposing changes in poverty over time into a growth and a redistributive component. See, for example, Chen and Wang (2001), Khan and Riskin (2001), Fang *et al*. (2002) and Hussain (2003). In all these studies, the spatial variation of urban poverty is only treated in passing. The method used for decomposition follows Datt and Ravallion (1992), and is subject to the two limitations discussed above.

The remainder of the paper is organized as follows. Section 2 shows how the semi-parametric approach to deriving the Lorenz curve can be used under the Shapley value decomposition framework to measure and decompose poverty. Section 3 introduces data and compares the poverty rates estimated by the semi-parametric approach and those based on three parametric models. In section 4, the decomposition results are discussed. The last section concludes.

2 Methodology

Poverty can be measured along a number of dimensions. This paper focuses on income poverty measured by the head count ratio. For a given subsistence level of income z, the poverty rate H is determined by the average level of nominal income μ and the Lorenz curve L. If we use the subscript '0' to denote the national income distribution, then the deviation of poverty rate in province i from the national poverty rate can be expressed as:

$$\Delta H_i = H(\mu_i, L_i, z) - H(\mu_0, L_0, z)\,. \tag{1}$$

Thus, the total difference between the provincial and the national poverty rates arises from the differences in two factors: the average income μ and the distribution of income L.

To separate the effects of these two factors, Datt and Ravallion (1992) defines the contribution of income differences as:

$$\Delta H_i(\mu) = H(\mu_i, L_r, z) - H(\mu_0, L_r, z)\,, \tag{2}$$

and the contribution of inequality differences as

$$\Delta H_i(L) = H(\mu_r, L_i, z) - H(\mu_r, L_0, z)\,, \tag{3}$$

where r can be either i or 0 as long as it is consistent across the two equations. The problem with this decomposition is that $\Delta H_i(\mu)$ and $\Delta H_i(L)$ do not add up to ΔH_i. In cases where the discrepancy is large, the decomposition would leave unexplained the bulk of the difference in poverty. Furthermore, the decomposition results vary with the choice of the reference point r, and there is no guidance on how to choose one over the other. The problem is compounded when wide regional diversity in consumption patterns, living standards and price levels makes the relative level of nominal income a poor indicator for welfare comparison. In such cases, individual regions would have distinct poverty lines z_i, which would usually differ from the national poverty line z_0 as well. The results of decomposition according to equations (2) and (3) would be affected by the choices of the reference L, μ and z, all of which need not be from the same distribution.

The Shapley value decomposition, proposed in Shorrocks (1999) and applied in Kolenikov and Shorrocks (2005) to analyse regional poverty in Russia, overcomes the problem. The rationale and explanations of the decomposition can be found in these two papers. In the current context, finding the Shapley value of the contribution to ΔH_i by regional differences in mean nominal income (inequality) amounts to considering the six possible sequences of replacing μ_0, L_0 and z_0 with μ_i, L_i and z_i, and averaging the marginal effects of μ (L) over the six sequences.[1] That is, the income component and the inequality component of the regional poverty difference are respectively:

$$\Delta H_i(\mu) = \frac{1}{6}\left\{ \begin{array}{l} 2\left[H(\mu_i, L_0, z_0) - H(\mu_0, L_0, z_0)\right] + \left[H(\mu_i, L_i, z_0) - H(\mu_0, L_i, z_0)\right] \\ + \left[H(\mu_i, L_0, z_i) - H(\mu_0, L_0, z_i)\right] + 2\left[H(\mu_i, L_i, z_i) - H(\mu_0, L_i, z_i)\right] \end{array} \right\} \quad (4)$$

and

$$\Delta H_i(L) = \frac{1}{6}\left\{ \begin{array}{l} 2\left[H(\mu_0, L_i, z_0) - H(\mu_0, L_0, z_0)\right] + \left[H(\mu_i, L_i, z_0) - H(\mu_i, L_0, z_0)\right] \\ + \left[H(\mu_0, L_i, z_i) - H(\mu_0, L_0, z_i)\right] + 2\left[H(\mu_i, L_i, z_i) - H(\mu_i, L_0, z_i)\right] \end{array} \right\} \quad (5)$$

When $z_i \neq z_0$, ΔH_i has a third component due to regional differences in poverty lines. The Shapley value of the poverty line component is given by

$$\Delta H_i(z) = \frac{1}{6}\left\{ \begin{array}{l} 2\left[H(\mu_0, L_0, z_i) - H(\mu_0, L_0, z_0)\right] + \left[H(\mu_i, L_0, z_i) - H(\mu_i, L_0, z_0)\right] \\ + \left[H(\mu_0, L_i, z_i) - H(\mu_0, L_i, z_0)\right] + 2\left[H(\mu_i, L_i, z_i) - H(\mu_i, L_i, z_0)\right] \end{array} \right\} \quad (6)$$

Before implementing either of the above decomposition procedures, the Lorenz curve or the income density function must be identified. The standard approach calls for specifying a functional form modelling either the Lorenz curve or the density function. For example, Datt and Ravallion (1992) consider the Beta and the general quadratic (GQ) models for deriving the Lorenz curve. Kolenikov and Shorrocks (2005) make use of the lognormal distribution. The estimated parameters are then used to compute various poverty measures, including the head count ratio. The parametric approach is appropriate only if the postulated functional form is a reasonable approximation of the underlying income distribution. In empirical applications, simple models of income distribution such as the two-parameter lognormal distribution proved poor fit to the data (McDonald 1984). More sophisticated models with a larger set of parameters may improve the goodness of fit, but only at the cost of increased difficulty in estimation and interpretation. The estimation of the Lorenz curve suffers from similar problems. The estimated Beta and GQ models, in particular, do not always qualify as Lorenz curves. They are especially vulnerable at the lower section of the Lorenz curve, the very part of the income distribution that poverty measurement is concerned with.[2] Another

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1 Datt and Ravallion (1992) also note that averaging over alternative reference distributions would cancel out the residual term, but consider this ‘arbitrary’.

2 For the function $l = L(p)$, where l and p denote the cumulative income and population shares respectively, to be a valid Lorenz curve, the following conditions must hold: (1) $L(0) = 0$; (2) $L(1) = 1$; (3) $L'(0^+) \geq 0$; (4) $L''(p) \geq 0$, for $0 < p < 1$. The third and fourth conditions translate into non-linear inequality restrictions on the parameters of the Beta and GQ models. In empirical

disadvantage of the parametric approach is that data contamination in the upper tail can bias parameter estimates, and hence distort poverty measures which are only related to the bottom of the income distribution.

A possible way to avoid the pitfalls of the parametric approach is to discard parametric restrictions completely and adopt the non-parametric method of kernel density estimation. Alternatively, one can mitigate the problem by introducing more flexibility into the parametric approach. The data-generating procedure proposed by Shorrocks and Wan (2004) offers an example of the latter. The procedure starts with a parametric model. In principle, this may be any plausible Lorenz curve or density function that can be estimated from the available number of data points. The lognormal distribution is used in this paper. Shorrocks and Wan (2004) report that for quantile data the procedure works well with the lognormal distribution. Given a set of quantiles, an estimate of the variance of the logarithmic income σ can be obtained using the special property of the lognormal distribution. The estimated variance is then used to generate an initial set of income levels spread evenly over the lognormal distribution $LN(1, \sigma)$. The rest of the procedure is non-parametric and consists in: (1) divide the generated data into groups in accordance with the reported quantiles; (2) scale the generated incomes quantile by quantile, starting from the middle part of the distribution, so that the group means of the generated observations match the reported means. Shorrocks and Wan (2004) show that altering the number of data points in the generated sample may have some effect on the curvature of its Lorenz curve, but that a sample size of 1,000 or above is generally sufficient to track the true Lorenz curve well. In our application below, we use 5,000 as the benchmark sample size, i.e., we generate 5,000 data points for each of the 28 provinces in our sample. The national sample is compiled by randomly drawing from each provincial sample the number of observations in proportion to its share in the total urban population of the 28 provinces. With the generated data set, calculating the head count ratio is simply a matter of comparing each income with the appropriate poverty line and counting the number of incomes that fall below the poverty line.

Compared with the parametric approach and the usual non-parametric approach, the Shorrocks-Wan procedure has three clear advantages. First, the lognormal model is only invoked to produce the initial data points. The scaling process that follows allows some flexibility as to what form the final distribution may take. The risk of committing misspecification errors is therefore reduced since the actual data are not forced into a rigid 'mould'. Second, the upper and lower parts of the Lorenz curve are scaled separately. This compartmentalization helps contain the distortionary effect of data contaminations in the upper tail of the income distribution. Third, the procedure only requires grouped income data, and as such is especially useful when more disaggregated data are not available.

applications, violations of the last two conditions mostly occur at the bottom section of the Lorenz curve. For example, in their simulations using Current Population Survey data, Shorrocks and Wan (2004) found that the estimated Beta and GQ curves may dip into the fourth quadrant.

3 Data and poverty rate estimates

To illustrate the semi-parametric decomposition method, we apply it to data from the 1998 urban household survey in China. We were unable to obtain data from the National Bureau of Statistics (NBS), the official body administering the survey. Instead, our data were collected from provincial statistic yearbooks. Our sample comprises 25 provinces and 3 cities of provincial status. Chongqing, Gansu and Tibet are excluded due to the incompleteness of data.[3]

The published data are reported in the form of household quantiles rather than population quantiles, and the partition of quantiles is not uniform across provinces. For the majority of provinces, the average household size of each household quantile is available, enabling us to convert household quantiles into population quantiles. Where household sizes are not reported, household quantiles are used to approximate population quantiles.[4] Because low-income groups tend to have larger households than the rest of the population, the approximation may lead to underestimation of the poverty rate. The income shares were derived from per capita mean incomes reported for household quantiles, making use of the population shares obtained earlier. Disposable income is used wherever it is available, and is proxied by total income where it is not. In the latter case, the estimated poverty rate would also be biased downward. The bias is unlikely to be serious, however, since the difference between disposable income and total income is rather small in urban China.[5]

The main reason for choosing the year 1998 is the lack of appropriate provincial poverty lines for other years. There do exist official poverty lines for different localities. But these are set by local governments using a multitude of methods, and are greatly influenced by the size of local coffers (Hussain 2003). Earlier studies on urban poverty have experimented with the PPP-adjusted US$1 or US$2 per day poverty lines. However, adopting a single poverty line for all provinces would entail glossing over the large regional differences in living standards, which is particularly problematic for a study like ours. Even controlling for regional price differences will not provide a satisfactory answer, since consumption patterns diverge widely across regions. Using detailed household-level data, Hussain (2003) reports for all 31 provinces the 1998 urban poverty lines constructed according to a standard procedure. These poverty lines will be used for the empirical analysis below.

As a first assessment of the performance of our proposed method, the 1998 urban poverty rates for the 28 provinces are estimated using the semi-parametric method and the parametric Beta, GQ and lognormal models in turn. The estimates are tabulated in the left-hand side of Table 1, where the head count ratios calculated by Hussain are also

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3 For discussion about the shortcomings of the NBS urban survey data with respect to poverty measurement, see Hussain (2003).

4 The differences between household quantiles and the derived population quantiles do not seem to follow any pattern, offering no indication of how population quantiles might be adjusted to improve the approximation.

5 Neither do we have total income data for all provinces. For provinces with data on both income measures, replacing disposable income with total income leaves all results unchanged.

listed to serve as the benchmark.[6] Shown on the right of Table 1 are the deviations of the estimates from the benchmark poverty rates. The last row shows the average absolute deviation of each method.

The following points about Table 1 are noteworthy. First, with few exceptions, the estimated poverty rates across all the four methods fall below the benchmark rates. This is not unexpected, considering that the benchmark rates are based on disposable income while for a number of provinces we had to substitute total income for disposable income. Moreover, the direction of deviation is highly consistent especially among the semi-parametric, Beta and GQ methods. This suggests that part of the deviations arise from the differences between our and Hussain's datasets, and are thus independent of the methods used.

Second, the estimated Beta and GQ models do not always satisfy the theoretical conditions for a valid Lorenz curve. Such cases are marked as 'n.a.' in Table 1. A quick count indicates that the two models are not applicable for over 10 per cent of the provinces. If we use absolute deviations from the benchmark poverty rates as the yardstick of the performance of the four methods, the lognormal model is preferable to the two Lorenz curve models on average. On the province-by-province basis, it outperforms the Beta model but is slightly inferior to the GQ model in over half of the cases where the latter is valid. The semi-parametric method improves upon the lognormal model, delivering the smallest average deviation and also surpassing the other three models in more than half of the individual cases.

Finally, our estimate of the national poverty rate is higher than the benchmark, while the majority of our estimates for individual provinces are lower than the benchmark. This occurred partly because different methods were involved in calculating the national poverty rate. The benchmark national rate is the average of the provincial rates, weighted by the provincial shares of total urban population. We have chosen to assemble a national sample out of the generated provincial samples and to compute a national poverty line as the weighted average of the provincial poverty lines. The national poverty rate was then obtained as the proportion of incomes below the national poverty line in the national sample. Maintaining a consistent method for calculating provincial and national poverty rates enables us to conduct counterfactual analysis required by the Shapley decomposition procedure. The national poverty rates from the parametric models are based on grouped data at the national level. They are significantly lower than the rate estimated by the semi-parametric method. This will have an impact on the results of the decomposition analysis. We will return to this point below.

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6 Although Hussain's poverty rates provide a reasonable profile of urban poverty in China, we have doubts about some of them. For instance, it is counterintuitive that the poverty rate of Guizhou, the poorest province in terms of per capita GDP, is lower than the poverty rate of the rich city Tianjin. It should be noted that the poverty lines in Hussain (2003) are constructed from expenditure data, which are usually more reliable than income data. We feel that the 'counterintuitive' poverty rates have more to do with problems in the income data than with biases in the poverty lines. In the decomposition analysis that follows, the influence of poverty line is separated from that of mean income and inequality. Even if the poverty lines are biased, the decomposition results concerning mean income and inequality are likely to remain unaffected.

Overall, the poverty rates estimated with the semi-parametric method lie within reasonable ranges of the benchmark rates, though there are large discrepancies in several cases. As mentioned above, some of our estimates may be biased due to the use of total income and equal household size. Such biases will not be fully carried over to the decomposition results below, however. The way our national sample is constructed entails that an overestimation of income levels in a provincial sample is reflected proportionally in the national sample. The overestimations in both samples cancel out to some extent when the difference in provincial and national poverty rates is decomposed. The results in Table 1 indicate that the semi-parametric method not only has wider applicability than the parametric models, it also provides better relative fit in terms of matching the poverty rates calculated from household-level survey data. It is also evident that, judging by any of the five sets of estimates, there is considerable variation in provincial urban poverty rates.

4 Results of spatial decomposition

Applying the decomposition specified in equations (4)–(6) partitions the difference between a provincial poverty rate and the national poverty rate into its 'mean income', 'inequality' and 'poverty line' components. The first component indicates what difference would remain if the provincial and national poverty lines and Lorenz curves were identical. The second component gives the average difference that would occur if the province and the nation had the same mean incomes and poverty lines. The third component identifies the difference caused by the use of distinct provincial and national poverty lines. The decomposition was carried out under each of the four methods discussed in section 3, and the results are reported in Table 2.

When the semi-parametric method is implemented to estimate the distribution of relative income, the average level of nominal income is found to be the most important factor affecting the poverty rate. The magnitude of the mean-income component is the greatest (in absolute value) among the three components for 13 out of the 28 provinces. The influence of the poverty line is dominant for 6 provinces. Not surprisingly, the effects of the mean income and the poverty line tend to work in opposite directions, a reflection that high costs of living often accompany high income, though the causality can go both ways. For about a third of the provinces, the distribution of relative income is the principal determinant of the poverty rate.

Comparing the decomposition results of the semi-parametric approach with those of the parametric models, the difference that immediately comes to attention is that the parametric models record far fewer provinces with poverty rates lower than the national level. The primary reason for this difference is, as mentioned earlier, that the nationwide poverty rates for the parametric models are calculated from grouped data at the national level, while those for the semi-parametric method are based on a generated national sample. Whether the grouped data or the generated sample is more representative of the national income distribution remains an open question. In the context, the choice between them apparently has an impact on the assessment of how the distribution of relative income affects poverty. The generated sample incorporates both the inequalities within individual provinces and the inequality between them. As such, inequality at the national level would be higher than at the provincial level if between-province inequality is more significant than within-province inequality. An indication of whether that is the case for our sample is the signs of the inequality components. For the semi-parametric method, a negative sign means that, after controlling for the differences in mean incomes and poverty lines, the bottom tail of the provincial income distribution is thinner than that of the national distribution. While this does not necessarily imply that overall the provincial distribution is more equal than the national distribution, it does suggest that at least the bottom section of the provincial Lorenz curve lies above that of the national Lorenz curve. For the parametric models, the inequality component is directly linked to the model parameters determining the shape of entire distributions. A negative sign thus implies that the provincial distribution is less dispersed than the nation-wide distribution. As shown in Table 2, the inequality components estimated using the semi-parametric method are mostly negative, signifying lower inequality at the provincial level. This feature does not seem to present itself in the decomposition results of the parametric models where provincial inequality levels are mostly higher than the national level, and so are provincial poverty rates. Although we consider the results from the semi-parametric method accord better with intuition and existing research on China's regional inequality, it is perhaps more appropriate to suspend judgement until more informative datasets become available. Despite the discrepancies in the results about the inequality component, the magnitudes and signs of the income and poverty line components are quite similar across the four methods. Henceforth, the discussion will focus on the results of the semi-parametric method. Needless to say that all inferences concerning only the mean income and poverty line components can also be made for the parametric models, while inferences involving the inequality component apply merely to the results of the semi-parametric method.

A recurring theme in the studies about China's income distribution is growing regional disparity in the era of economic reform. An enlarged coastal-interior divide has been observed and concerns raised about its ramifications for poverty alleviation (Kanbur and Zhang 2001). Therefore, it is of much interest to investigate whether the contributions of the three components to the spatial variations of poverty also display regional patterns. To do this, we have divided the provinces into three geographical groups: coastal, central and western. The decomposition results in Table 2 are reproduced in Figure 1 for ease of comparison.

An inspection of Figure 1 reveals that there is as much commonality as heterogeneity among the group members. In the coastal region, the costs of living are higher not only in the rich cities and provinces of Guangdong, Shanghai, Beijing, Zhejiang, Tianjin and Fujian, but also in the poor ones like Guangxi, Hebei and Hainan. While high incomes, aided by relatively low inequality, enable the rich provinces to still enjoy poverty rates lower than the national level, poor provinces are only helped by their more pro-poor income distributions. In both cases there is one instance – Tianjin in the first case and Hainan in the second case – where the effects of high income or 'better' distribution are outweighed by the poverty-increasing effects of other factors.

In the central region, provincial nominal incomes are uniformly lower than the national average, yet provincial poverty rates are all lower than the national rate. For some provinces of the group, lower poverty is mainly ascribable to greater shares of the poor in total income; for others, low costs of living are the chief ameliorating factor. In all provinces, however, the inequality and the poverty line components work in the same direction.

The western provinces tend to have more ‘adverse’ income distributions than do those in the other two groups. The inequality components are either small in absolute value or positive. This group also seems to be more diverse. For example, Yunnan province is better placed with the coastal group and the decomposition for Sichuan province is more similar to those for the central provinces.

The above findings have three implications for policy measures aimed at alleviating urban poverty in China. First, there is a geographical dimension to the explanation of the variation of poverty rates across provinces. Policy measures with region-specific focus are thus advisable. For the coastal provinces, the significant influence of high costs of living calls for attention to the havoc that inflation may cause on the poor; for the central provinces, the emphasis should be placed on raising nominal income; for the western provinces, efforts to increase income shall be supplemented by redistribution policy. Second, the provinces within each group are still quite heterogeneous, suggesting that geographical features such as distance to the sea, climate, topography of the terrain, and so on, are not the sole determinants of regional grouping. Much of the similarity and dissimilarity among the provinces can be traced to their industrial structures and the past and recent economic policies (Kanbur and Zhang 2001). Thus, further to the first point, if region-targeting policies were to be implemented, the division of regions shall not necessarily be based on geographical locations. The central province of Shanxi, for instance, share more similarities with the western provinces of Guizhou, Qinghai, Shaanxi and Ningxia. The coastal group may well be split in two, with Shandong, Guangxi, Hebei and Hainan in one group, the western province of Yunnan joining the rich cities and provinces in the second group, and Liaoning province left out. Finally, most of the regional differences in poverty rates are still due to disparities in nominal income. As far as reducing regional disparities in poverty rates is concerned, therefore, there seems to be no alternative to faster income growth in the lagging provinces. However, consideration should also be given to the potential role of redistribution policy, especially for those western provinces where inequality tends to be relatively high.

Since the importance of pursuing income growth is reinforced by the decomposition results, a closely related question is how fast income growth can reduce the absolute levels of poverty, say, halve the current poverty rates, in different provinces? The actual outcome will of course depend on the rate of income growth itself as well as on how the distribution of relative income will change in the process. Nonetheless, an assessment of the likely effects of income growth can be made by calculating the elasticity of poverty with respect to distribution-neutral growth, which is defined as the percentage of the poor whose incomes will rise above a given poverty line if the incomes of all groups in the society increase simultaneously by 1 per cent. Table 3 lists, for each province in our sample, the growth elasticity of poverty and the number of years it would take to reduce the poverty rate by half if nominal income increases by 5 per cent per annum, the national average growth rate of urban per capita income in 1997–98. All other things being equal, the last column of Table 3 suggests that most Chinese provinces should have halved their 1998 urban poverty rates by now if the 5 per cent annual growth rate of nominal income had been sustained and income distribution unchanged.

Note that the magnitude of an income component (as shown in Table 2) does not bear directly on the magnitude of the growth elasticity for the corresponding province. The former is mostly determined by the differences in the mean incomes and poverty rates between the provincial level and the national average. The latter depends on the location of the provincial poverty line along the provincial income distribution and on the shape of the distribution around the poverty line. In the literature, the indicators used to convey such information are usually the ratio of the mean income to the poverty line together with an inequality index such as the Gini coefficient. See, for example, Heltberg (2002). The second and third columns of Table 3 provide the mean income/poverty line ratios and the Gini coefficients of the generated provincial income samples.[7] By and large, the figures in Table 3 show that provinces with higher mean income/poverty line ratios and smaller Gini coefficients would see faster poverty reduction for a given rate of income growth. However, closer scrutiny reveals a few 'irregularities'. The Gini coefficients of Hainan and Guizhou are nearly of equal magnitudes. Yet the growth elasticity of poverty is higher for Hainan despite its mean income/poverty line ratio being lower. The same pattern also exists for two other pairs of provinces: Hunan and Jilin, and Guangdong and Sichuan. To explain this apparent abnormality, recall that the growth elasticity of poverty is affected by the part of the income distribution that is below and around the poverty line. The shape of the bottom tail of a distribution does not find exact correspondence in the value of the Gini coefficient, which is an inequality index of the entire distribution. As it turns out, the decomposition results in Table 2 can provide supplementary information in such cases. For instance, the inequality component of Hainan is greater (in absolute value) than that of Guizhou, implying a more compacted bottom tail of the income distribution, and thus higher growth elasticity, for Hainan.

5 Conclusion

Poverty decomposition can provide useful insights into the variations of poverty over time and across regions. This paper proposes a semi-parametric approach to poverty decomposition which improves on the popular method of Datt and Ravallion (1992) in two aspects. First, simulated household samples are obtained using the procedure of Shorrocks and Wan (2004). This helps to contain misspecification bias associated with the arbitrariness in choosing the functional form for the parametric Lorenz curve or income distribution model. Second, our method makes use of the Shapley value framework of Shorrocks (1999), thus removing the risk of overlooking a potentially important residual term.

The proposed method is applied to analysing poverty in urban China, based on grouped household survey data at the provincial level. The variations of urban poverty rates across the Chinese provinces are decomposed into the contributions by the differences in three factors: average nominal incomes, distributions of relative income and poverty lines. For most provinces in our sample, the decomposition results give prominence to the role of average nominal income in determining the incidence of poverty. Thus, there is no escaping, for provinces with relatively high poverty rates, the need to devote greater effort to attaining fast and sustained income growth if regional disparity in

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7 It is interesting to note that if the nominal income/poverty line ratio was considered real income, the ranking of the development levels of the provinces would be completely different from that based on nominal income. For example, Xingjiang and Qinghai, with average nominal incomes ranking 12th and 23rd respectively, would become the first and third most affluent provinces, whereas Shanghai, with the second highest nominal average income, would fall to the 12th place.

poverty was to be reduced. The influence of distribution should not be dismissed easily, however. Better-than-average distribution is the main factor for about a third of the provinces in keeping their poverty rates below the national average. For the purpose of prioritizing income growth and redistribution policies, the question that remains here is the relationship between average income and the level of inequality. Interestingly, our decomposition results suggest that while the rich provinces do not seem to suffer particularly from high inequality, distributions in the poorest provinces do tend to be more adverse for the poor. Whether this pattern in the cross-section data also exists in the time profile of changes in poverty, income and inequality is clearly where more future research is needed.

The decomposition results also exhibit a regional pattern. The differences in poverty lines, part of which are attributable to differences in the costs of living, go a long way towards bringing closer the poverty rates in the richest coastal provinces and those in some poor western provinces. The lower average level of poverty in the central provinces than in the western provinces is mostly a result of the lower level of inequality in the former region. It is also seen that, as far as the determinants of poverty rates are concerned, the conventional division of the provinces into geographical groups does not appear to be the best way of categorizing them. Important forces other than the geographical features of the provinces are also at work, and the distributions of these forces may not coincide with physical locations. These regional characteristics reduce the value of blanket national poverty reduction strategies, suggest a region-specific approach and further, for this approach to be more effective, the need to take into account non-geographical factors in grouping the provinces.

The performance of the semi-parametric method is compared with that of three parametric models: the Beta and GQ models and the lognormal model of income distribution. Using the poverty rates in Hussain (2003) as the benchmark, it is found that the semi-parametric method provides better fit both on average and on individual basis. The semi-parametric method also obviates the need to impose non-linear restrictions during estimation. As our results show, the failure to impose these restrictions can lead to invalid parameter estimates in the Beta and GQ models. The semi-parametric method can be readily used to conduct poverty decomposition along the time dimension. We intend to pursue this in future research.

References

Chen, S. and Y. Wang (2001). 'China's Growth and Poverty Reduction: Recent Trends Between 1990 and 1999'. Paper presented at WBI-PIDS Seminar on *Strengthening Poverty Data Collection and Analysis.* Manila, The Philippines, 30 April–4 May.

Datt, G. and M. Ravallion (1992). 'Growth and Redistribution Components of Changes in Poverty Measures: A Decomposition with Application to Brazil and India in the 1980s'. *Journal of Development Economics*, 38: 275-95.

Fang, C., X. Zhang and S. Fan (2002). 'Emergence of Urban Poverty and Inequality in China: Evidence from Household Survey'. *China Economic Review*, 13: 430-43.

Heltberg, R. (2002). 'The Poverty Elasticity of Growth'. *Discussion Paper No. 2002/21*. World Institute for Development Economics Research, United Nations University: Helsinki, Finland.

Hussain, A. (2003). *Urban Poverty in China: Measurement, Patterns and Policies.* International Labour Organisation: Geneva.

Kanbur, R. and X. Zhang (2001). 'Fifty Years of Regional Inequality in China: A Journey Through Revolution, Reform and Openness'. *Discussion Paper No. 2887*, Centre for Economic Policy Research: London.

Khan, A. R. and C. Riskin (2001). *Inequality and Poverty in China in the Age of Globalization*. Oxford University Press: New York.

Kolenikov, S. and A. Shorrocks (2005). 'A Decomposition Analysis of Regional Poverty in Russia'. *Review of Development Economics*, 9(1): 25-46.

McDonald, J. B. (1984). 'Some Generalized Functions for the Size Distribution of Income'. *Econometric,* 52: 674-64.

Shorrocks, A. (1999). 'Decomposition Procedures for Distributional Analysis: A Unified Framework Based on the Shapley Value'. Mimeo. University of Essex.

Shorrocks, A. and G. Wan (2004). 'A Simple Method for Generating Income Data from Lorenz Coordinates'. Mimeo. World Institute for Development Economics Research, United Nations University: Helsinki, Finland.

Table 1
Estimated poverty rates

	Hussain	Semi-parametric	Beta	GQ	Lognormal	Deviations Semi-parametric	Deviations Beta	Deviations GQ	Deviations Lognormal
Anhui	2.89	2.38	2.13	1.89	2.28	-0.51	-0.76	-1.00	-0.61
Beijing	0.73	0.36	n.a.	n.a.	0.62	-0.37	n.a.	n.a.	-0.11
Fujian	2.18	0.70	1.15	n.a.	1.32	-1.48	-1.03	n.a.	-0.86
Guangdong	0.68	1.46	n.a.	n.a.	0.94	0.78	n.a.	n.a.	0.26
Guangxi	3.01	4.34	5.02	5.70	4.42	1.33	2.01	2.69	1.41
Guizhou	5.00	7.38	6.66	7.75	6.84	2.38	1.66	2.75	1.84
Hainan	7.94	7.58	8.18	9.11	7.44	-0.36	0.24	1.17	-0.50
Hebei	5.20	5.28	5.39	6.54	6.58	0.08	0.19	1.34	1.38
Heilongjiang	6.92	5.06	5.07	6.41	5.48	-1.86	-1.85	-0.51	-1.44
Henan	8.39	4.36	4.40	5.58	4.52	-4.03	-3.99	-2.81	-3.87
Hubei	5.67	4.20	4.22	5.07	3.84	-1.47	-1.45	-0.60	-1.83
Hunan	3.61	2.22	1.82	1.00	2.26	-1.39	-1.79	-2.61	-1.35
Inner Mongolia	6.40	4.38	4.15	5.06	4.42	-2.02	-2.25	-1.34	-1.98
Jiangsu	1.20	1.16	n.a.	n.a.	0.70	-0.04	n.a.	n.a.	-0.50
Jiangxi	3.42	1.26	1.28	0.26	1.88	-2.16	-2.14	-3.16	-1.54
Jilin	7.54	3.48	3.44	4.03	3.24	-4.06	-4.10	-3.51	-4.30
Liaoning	6.13	6.34	6.05	7.02	6.86	0.21	-0.08	0.89	0.73
Ningxia	13.51	11.56	11.72	12.54	11.54	-1.95	-1.79	-0.97	-1.97
Qinghai	5.63	2.32	2.45	2.97	1.66	-3.31	-3.18	-2.66	-3.97
Shaanxi	11.95	8.96	7.81	8.95	7.20	-2.99	-4.14	-3.00	-4.75
Shandong	5.05	4.48	4.11	4.88	4.72	-0.57	-0.94	-0.17	-0.33
Shanghai	3.24	2.26	1.84	0.75	1.58	-0.98	-1.40	-2.49	-1.66
Shanxi	7.17	3.82	3.59	4.06	3.96	-3.35	-3.58	-3.11	-3.21
Sichuan	4.72	2.52	1.47	1.20	1.28	-2.20	-3.25	-3.52	-3.44
Tianjin	6.77	5.90	4.74	5.90	5.42	-0.87	-2.03	-0.87	-1.35
Xinjiang	6.16	4.44	4.20	4.68	3.82	-1.72	-1.96	-1.48	-2.34
Yunan	3.69	2.00	2.09	2.61	1.58	-1.69	-1.60	-1.08	-2.11
Zhejiang	1.62	1.00	n.a.	n.a.	1.48	-0.62	n.a.	n.a.	-0.14
National	4.73	5.71	2.73	3.06	3.20	0.98	-2.00	-1.67	-1.53
Average absolute deviation						1.58	1.98	1.89	1.77

Table 2
Decomposition of head count ratios

	Semi-parametric method			Beta Model			GQ Model			Lognormal model		
	Mean income	Inequality	Poverty line	Mean income	Inequality	Poverty line	Mean income	Inequality	Poverty line	Mean income	Inequality	Poverty line
Anhui	3.10	-4.80	-1.63	n.a.	n.a.	n.a.	3.41	-2.61	-1.97	2.24	-1.86	-1.29
Beijing	-6.28	-4.24	5.16	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	-6.25	-1.28	4.95
Fujian	-2.23	-3.38	0.60	-1.70	-0.35	0.47	n.a.	n.a.	n.a.	-2.29	-0.17	0.59
Guangdong	-8.32	-1.61	5.68	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	-7.04	-0.02	4.81
Guangxi	0.59	-3.35	1.39	0.18	0.43	1.68	0.23	0.20	2.21	0.17	-0.60	1.65
Guizhou	4.67	-1.24	-1.76	3.94	1.71	-1.73	4.81	1.99	-2.12	4.23	1.30	-1.88
Hainan	3.35	-3.04	1.56	2.82	0.94	1.69	3.23	0.89	1.93	2.72	-0.11	1.63
Hebei	2.05	-4.29	1.81	1.44	-0.60	1.83	1.88	-0.79	2.39	1.53	-0.10	1.95
Heilongjiang	6.81	-1.50	-5.97	n.a.	n.a.	n.a.	6.41	2.48	-5.54	5.40	1.61	-4.72
Henan	6.10	-2.94	-4.52	n.a.	n.a.	n.a.	6.44	0.93	-4.85	5.58	0.05	-4.30
Hubei	3.40	-4.50	-0.41	2.34	-0.62	-0.24	3.15	-0.82	-0.31	2.31	-1.42	-0.23
Hunan	0.36	-2.57	-1.28	-0.04	0.05	-0.93	-0.07	-0.28	-1.71	-0.04	0.21	-1.10
Inner Mongolia	5.80	-1.38	-5.75	n.a.	n.a.	n.a.	5.74	2.23	-5.96	4.73	1.44	-4.94
Jiangsu	-1.11	-2.87	-0.57	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	-1.11	-0.98	-0.39
Jiangxi	5.23	-4.85	-4.83	n.a.	n.a.	n.a.	6.12	-2.81	-6.12	4.27	-1.39	-4.19
Jilin	6.75	-3.12	-5.87	n.a.	n.a.	n.a.	6.73	0.25	-6.00	5.19	-0.47	-4.68
Liaoning	4.81	-2.88	-1.30	3.89	0.56	-1.13	4.93	0.44	-1.42	3.98	0.83	-1.15
Ningxia	8.68	0.49	-3.32	7.99	3.87	-2.88	8.30	4.22	-3.04	8.09	3.24	-2.98
Qinghai	5.42	-0.08	-8.73	n.a.	n.a.	n.a.	5.86	3.72	-9.68	4.47	1.03	-7.03
Shaanxi	8.42	-0.98	-4.20	6.42	2.12	-3.46	7.09	2.63	-3.83	6.42	1.12	-3.54
Shandong	0.73	-4.16	2.20	0.16	-0.81	2.02	0.22	-1.23	2.82	0.17	-0.84	2.19
Shanghai	-9.91	-4.03	10.48	n.a.	n.a.	n.a.	-13.01	-1.79	12.49	-10.38	-1.39	10.16
Shanxi	7.23	-0.95	-8.17	n.a.	n.a.	n.a.	7.40	2.68	-9.07	6.12	2.10	-7.45
Sichuan	1.52	-2.19	-2.52	n.a.	n.a.	n.a.	1.51	0.02	-3.40	0.84	-0.92	-1.84
Tianjin	-5.49	-0.50	6.18	n.a.	n.a.	n.a.	-7.04	2.97	6.90	-5.98	2.37	5.84
Xinjiang	1.75	3.02	-6.04	n.a.	n.a.	n.a.	1.22	6.23	-5.84	0.95	4.17	-4.49
Yunan	-1.57	-2.43	0.29	-1.45	0.52	0.28	-2.34	1.44	0.45	-1.50	-0.41	0.29
Zhejiang	-6.10	-3.37	4.75	n.a.	n.a.	n.a.	n.a.	n.a.	n.a.	-5.86	-0.29	4.44

Table 3
Growth elasticity of poverty

	Poverty line	Mean income / Poverty line	Gini coefficient	Growth elasticity	Years needed to halve poverty with 5% growth
Anhui	2138	2.23	0.20	-6.72	1.69
Beijing	3118	2.73	0.19	-11.11	0.85
Fujian	2416	2.71	0.20	-8.57	1.24
Guangdong	3061	2.89	0.25	-4.11	3.01
Guangxi	2507	2.16	0.24	-2.30	5.66
Guizhou	2137	2.14	0.23	-2.17	6.04
Hainan	2465	1.99	0.23	-3.69	3.39
Hebei	2509	2.04	0.22	-4.17	2.97
Heilongjiang	1878	2.29	0.24	-4.35	2.83
Henan	1904	2.22	0.20	-2.29	5.69
Hubei	2283	2.12	0.22	-6.67	1.71
Hunan	2146	2.55	0.22	-4.50	2.72
Inner Mongolia	1824	2.39	0.24	-3.65	3.44
Jiangsu	2228	2.72	0.26	-6.90	1.64
Jiangxi	1809	2.36	0.20	-7.94	1.37
Jilin	1831	2.30	0.22	-5.75	2.05
Liaoning	2203	2.10	0.24	-4.10	3.02
Ningxia	2093	1.98	0.25	-2.25	5.81
Qinghai	1484	2.86	0.24	-7.76	1.41
Shaanxi	2014	2.10	0.22	-4.46	2.74
Shandong	2566	2.11	0.21	-4.91	2.46
Shanghai	3636	2.43	0.21	-5.31	2.25
Shanxi	1616	2.54	0.24	-3.66	3.42
Sichuan	2004	2.56	0.25	-4.76	2.55
Tianjin	2993	2.38	0.24	-3.39	3.73
Xinjiang	1772	2.92	0.28	-4.50	2.72
Yunan	2359	2.59	0.23	-6.00	1.94
Zhejiang	2989	2.64	0.22	-8.00	1.36

Sources: Poverty lines are from Hussain (2003). The rest are authors' calculations.

Figure 1
Decomposition results by regions