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Explaining the Poverty Difference between Inland and Coastal China

A Regression-based Decomposition Approach

Guanghua Wan[1] and Yin Zhang[2]

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Abstract

This paper proposes a decomposition framework for quantifying contributions of the determinants of poverty to spatial differences or temporal changes in poverty. This framework is then applied to address the issue why poverty incidence is higher in inland than in coastal China. The empirical application requires household or individual income observations which, generally speaking, are not available. Thus, a data-generation method developed by Shorrocks and Wan is introduced to construct such observations from grouped income data. It is found that inland China is poorer than coastal China, mainly due to lower efficiency in resource utilization not to less endowment of resources. Also, trade became poverty-reducing in coastal China in the late 1990s but remained poverty-inducing in inland China. Policy implications are briefly discussed.

Keywords: poverty, regression-based decomposition, quantile, China
JEL classification: I32, D33, C43

[1]UNU-WIDER, Helsinki; [2]University of Dundee

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UNU World Institute for Development Economics Research (UNU-WIDER)
Katajanokanlaituri 6 B, 00160 Helsinki, Finland

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1 Introduction

It is commonly observed that poverty varies across space. This variation occurs not only between nations, but also between regions within a country and between groups of localities within a region. In China, for example, poverty is more severe in the west than elsewhere, and in the countryside than in the urban areas. If allowed to persist over a long time, the spatial difference in poverty can threaten social and political stability and economic growth, especially when it coincides with ethnic or religious divisions. To design and prioritize anti-poverty policy options, it is important to pin down the causes of such differences.

One approach that may be adopted for the above purpose is the decomposition popularized by Datt and Ravallion (1992) and extended by Zhang and Wan (2006). The decomposition breaks down poverty difference across space or over time into two components that are respectively associated with income growth and distributional changes. Thus, the results of Datt-Ravallion decomposition tell which, income growth or distributional changes, is more important in explaining poverty difference. However, income growth and distributional changes are policy outcomes. While the decomposition results can help identify the desired outcomes, they offer little insights into how to achieve them. Essentially, this is because the Datt-Ravallion framework is based on the mathematical relationship between the chosen poverty index and the mean and Lorenz curve of the income distribution. It does not, therefore, enable linking poverty or its variations with fundamental economic variables such as education, location, or globalization. To gage the impacts of these variables on poverty appeals for a decomposition framework that incorporates the structural relationship between poverty and its determinants.

We propose such a decomposition method in Section 2 of this paper, which can be used to quantify absolute and relative or percentage contributions of various factors to poverty difference. Another contribution of the paper is the introduction of a semi-parametric method for generating individual incomes from grouped data. This method is useful as household or individual level data are often not accessible for one reason or another, e.g., confidentiality. In the case of China, grouped income data are regularly published for most regions. To ungroup the data is not a difficult task, but achieving a good approximation to the underlying distributions does present some challenges (Shorrocks and Wan 2006). The data-generation method and related issues are discussed in Section 3. This is followed by empirically decomposing poverty differences between coastal and inland areas in urban China. Finally, in Section 5, major findings are summarized with a view to informing the formulation of poverty reduction policy for China in general and for the lagging west in particular.

2 A poverty decomposition framework

At an appropriately aggregated level, poverty level is determined by a vector of determinants $\mathbf{X}$. Let i and j index groups of localities (such as west and east China) and P denote a poverty index (such as the poverty gap or the head-count ratio), then we have

$$P_i = \mathbf{X}_i \boldsymbol{\beta}_i + e_i \tag{1a}$$

$$P_j = \mathbf{X}_j \boldsymbol{\beta}_j + e_j \tag{1b}$$

where $\boldsymbol{\beta}$s are vectors of parameters to be estimated, denoting the marginal impacts of ***X*** on *P*, and *e*s are disturbance terms. The poverty difference between localities in group *i* and those in group *j*, denoted by ΔP, is given by

$$\Delta P \equiv \bar{P}_i - \bar{P}_j = \bar{\mathbf{X}}_i \boldsymbol{\beta}_i - \bar{\mathbf{X}}_j \boldsymbol{\beta}_j \tag{2}$$

where variables with an overhead bar '-' indicate mean or average values,[1] e.g., $\bar{\mathbf{X}} = (\bar{x}_1, \bar{x}_2, ..., \bar{x}_K)$. Since it is always possible to write $\boldsymbol{\beta}_j = \boldsymbol{\beta}_i - \Delta\boldsymbol{\beta}$ and $\bar{\mathbf{X}}_j = \bar{\mathbf{X}}_i - \Delta\mathbf{X}$ equation (2) can be expressed as:

$$\Delta P = \bar{\mathbf{X}}_i \Delta\boldsymbol{\beta} + \boldsymbol{\beta}_i \Delta\mathbf{X} - \Delta\boldsymbol{\beta}\Delta\mathbf{X} \tag{3}$$

Alternatively, one can substitute $\boldsymbol{\beta}_i = \boldsymbol{\beta}_j + \Delta\boldsymbol{\beta}$ and $\bar{\mathbf{X}}_i = \bar{\mathbf{X}}_j + \Delta\mathbf{X}$ into (2) to obtain

$$\Delta P = \bar{\mathbf{X}}_j \Delta\boldsymbol{\beta} + \boldsymbol{\beta}_j \Delta\mathbf{X} + \Delta\boldsymbol{\beta}\Delta\mathbf{X} \tag{4}$$

Both (3) and (4) can be used to decompose ΔP. According to (3), the poverty difference is attributable to differences in the impacts of factor inputs given by $\bar{\mathbf{X}}_i \Delta\boldsymbol{\beta}$ and differences in factor endowments given by $\boldsymbol{\beta}_i \Delta\mathbf{X}$ plus an interactive term $\Delta\boldsymbol{\beta}\Delta\mathbf{X}$. On the other hand, by (4) the same poverty difference can be decomposed into components associated with differences in the impacts of factor inputs given by $\bar{\mathbf{X}}_j \Delta\boldsymbol{\beta}$ and differences in factor endowments given by $\boldsymbol{\beta}_j \Delta\mathbf{X}$ plus the same interactive term $\Delta\boldsymbol{\beta}\Delta\mathbf{X}$. Although the total poverty differences in (3) and (4) are identical, the decomposition components obtained usually differ depending on which expression, (3) or (4), is used. This is caused by the adoption of different reference points: group *i* is taken as the reference point in deriving (3) while group *j* is taken as the reference point in deriving (4). The problem of reference point is commonly encountered in the literatures on index numbers and on decomposition. The conventional practice is to arbitrarily choose one reference point.

To eliminate the arbitrariness in reference point selection, one possibility is to add (3) and (4) and take the average to arrive at

$$\Delta P = 0.5\left[(\bar{\mathbf{X}}_i + \bar{\mathbf{X}}_j)\Delta\boldsymbol{\beta} + (\boldsymbol{\beta}_i + \boldsymbol{\beta}_j)\Delta\mathbf{X}\right] \tag{5}$$

Since expressions (3) and (4) are equally justified or equally valid as mathematical expressions, the averaging procedure seems natural and reasonable. It is useful to note that the non-interpretable interactive term is no longer present in (5) and this represents

[1] It is also possible to write $\Delta P = P_i - P_j = \mathbf{X}_i \boldsymbol{\beta}_i - \mathbf{X}_j \boldsymbol{\beta}_j + e_i - e_j$. We prefer to use (2), largely inspired by Oaxaca (1973) and Blinder (1973) who developed the well-known wage decomposition framework. The advantage of using (2) lies in the absence of the troublesome disturbance terms.

an additional advantage of the averaging procedure. Comparing expression (5) with expressions (3) and (4), it is easy to see that the decomposition in (5) is symmetric regarding the reference point, ensuring the same and identical decomposition results irrespective of the reference point one decides to adopt.

The derivation of expression (5) may appear to be mundane arithmetic. Indeed, many decomposition methods in economics are outcomes of mathematical convenience to varying degrees. A case in point is the well-celebrated Solow's growth accounting where a change in total output is decomposed into factor contributions and a residual term called total factor productivity or TFP. In the income distribution literature, such examples include the classical decomposition of Theil-L inequality measure into within- and between-group components (Shorrocks and Wan 2005) and the decomposition of poverty indices by population subgroups (Foster and Shorrocks 1991). In all these examples, the variable (Y) whose change is to be decomposed can be express as the function of a number of other variables (**X**) as in $Y = f(\mathbf{X}, \boldsymbol{\beta})$, where $\boldsymbol{\beta}$ is the vector of the parameters of the function $f(\cdot)$. It just so happens that the particular functional form $f(\cdot)$ chosen by the researcher permits ΔY to be written as a linear additive function of $\Delta\overline{\mathbf{X}}$ and/or $\Delta\overline{\boldsymbol{\beta}}$. In other words, these decompositions are not derivable from any economic (usually optimizing) framework. And, their decomposability depends on the functional form $f(\cdot)$. This is, however, not the case with the decomposition in (5). As it turns out, equation (5) is the unique result that obtains if one uses cooperative game theory to allocate ΔP into various sources. For technical details, see Shorrocks (1999), and Shapley (1953).

Equation (5) is our final formula for decomposing poverty difference between two sub-groups of a population. This decomposition separates total difference in poverty into two broad components: the overall *endowment component* given by $0.5(\boldsymbol{\beta}_i + \boldsymbol{\beta}_j)\Delta\mathbf{X}$ and the overall *impact component* given by $0.5(\overline{\mathbf{X}}_i + \overline{\mathbf{X}}_j)\Delta\boldsymbol{\beta}$. In the absence of any difference in factor inputs (as represented by $\Delta\boldsymbol{X}$), the endowment component is nil and any poverty difference is entirely due to differing marginal impacts of $\boldsymbol{X}$ on P in different locations. Similarly, in the absence of any difference in the marginal impacts of $\boldsymbol{X}$ on P (as represented by $\Delta\boldsymbol{\beta}$), the impact component vanishes and any poverty difference is entirely attributable to gaps in endowments across locations. Of course, one can divide these components by ΔP so that the respective contributions become percentages, which are unit-free and comparable across different studies. It is easy to show that the overall endowment contribution can be broken down further into finer components associated with individual factors. By analogy, the impact component can be decomposed into finer components attributable to each marginal impact. In addition, one can add up the finer endowment and finer impact components that are associated with the same factor k and name the sum as the contribution of factor k.

Although we have characterized ΔP as the poverty difference between two locations, the decomposition framework of (5) can be readily applied to decomposing changes of poverty over time or poverty differences between population subgroups. For example, one can estimate (1) and (2) respectively for males (or male-headed households) and females (or female-headed households) and attribute the poverty difference between these two groups to relevant socioeconomic factors such as education, health, employment conditions, location and so on. The same goes with such cases as migrant versus non-migrant workers or families, ethnic minorities versus majorities, state-owned enterprise employees versus private enterprise employees, and so on. Exercises of this type can help answer some interesting and important questions: is a disadvantaged group really resource-poor (the endowment component dominating) or in fact being discriminated against (the impact component dominating)? If the group is resource poor, what resources are binding and how important is each of the resource constraints?

It should be noted that the proposed decomposition framework does not impose any restrictions on what poverty measures can be used. Of course, different measures of poverty will give rise to different decomposition results. But this inconsistency would be due entirely to the different properties of poverty measures, not the proposed decomposition methodology. Further, the poverty regressions (1a) and (1b) need not be strictly linear and additive. Transformation of the dependent variable can be accommodated in ways similar to the use of logarithmic wage as the dependent variable in a typical Oaxaca-Blinder decomposition. Finally, independent variables can be subject to transformations too. For example, both a linear and a quadratic term of a variable can be included in (1a) and/or (1b), allowing the impact of the variable on poverty to be nonlinear. In this case, the contribution of x to poverty difference is associated with two terms instead of one: the difference in the mean of x or $\overline{x}$ and the difference in the mean of squared x or $\overline{x}^2$.

3 Data generation

To analyze poverty difference across regional belts in China, it is necessary to obtain a poverty index for each province.[2] This requires household or individual level data, which are generally unavailable when a wide coverage over an extended period is considered. There are two government data sources for income observations at the household level: the National Bureau of Statistics (NBS) and the Ministry of Agriculture. The former conducts nationwide household surveys in both urban and rural China, while the latter does the same but only for rural China. Neither of these agencies publishes or releases unit-records unless a formidable amount of fee is paid. Even if cost is not an issue, they only provide data for a fraction of provinces and for limited years. Further, the data set from the Ministry of Agriculture is notoriously contaminated and its quality is questionable even after a tremendous amount of effort has been made to clean up the data (see Wan et al. 2003).

Fortunately, since the late 1980s NBS has published grouped income data for most regions and in most years. They are mainly in quantile form for urban China and in income class format for rural China. These data are based on nationwide household income surveys and are widely considered to be of acceptable quality. We choose to focus on urban China for two reasons. First, we are particularly interested in examining the impact of globalization on poverty and globalization is perceived to have affected urban households more than rural households in China. Second, data for urban China is more complete than for rural China. In fact, we are able to assemble quantile shares for 29 provinces for most of the years between 1988 and 2001.

2 In the Chinese administrative division system, provinces, autonomous regions and municipalities are all administrative units directly under the central government. For brevity, the terms 'region' and 'province' are used interchangeably in this paper to denote all three types of administrative division of provincial status.

The major obstacle lying between the quantile information and poverty estimates is how to convert quantile data to individual records. Alternative techniques exist for this kind of ungrouping exercise. Broadly speaking, they can be classified into three groups: non-parametric, parametric, and semi-parametric. A typical non-parametric method is kernel density estimation as applied in Sala-i-Martin (2002a,b) and Zhang and Wan (2005). Chotikapanich et al. (2007) present an example of the parametric approach. The method adopted in this paper, proposed by Shorrocks and Wan (2006), belongs to the third group.

The idea of data conversion is quite straightforward. Starting with assuming a particular statistical distribution of income, say lognormal, parameter estimates of the distribution can be obtained from the grouped data (Aitchison and Brown 1957). With the parameter estimates, any number of observations can be generated. However, the assumed distribution may not be appropriate, which can lead to errors in the synthetic data with possibly large margins. Earlier attempts to evaluate proposed data generation procedures often rely on how well the calculated inequality measures from the true and converted data match. This evaluation is insufficient if the research objective relies on individual records, say for poverty measurement, not simply for estimating the area under the entire Lorenz curve for inequality measurement. While a particular data generation procedure may produce inequality estimates very close to the true values, the individual observations may not match so well.

Shorrocks and Wan (2006) extend conventional approaches to converting quantiles to individual records. Relying on some120,000 income observations from the Current Population Survey (CPS) of the USA, they evaluate various statistical distributions for data ungrouping. An interesting finding is that while the Beta and Generalized Quadratic Lorenz functions used by Datt and Ravallion (1992) can produce good inequality estimates, they do not perform well as far as individual records matching are concerned. In fact, in a majority of cases, these Lorenz functions yield negative predicted incomes and sometimes the estimated Lorenz curves are not monotonic. According to Shorrocks and Wan (2006), the three-parameter distributions of Singh-Maddala and Generalized Beta are not as accurate as the simple lognormal distribution in terms of income share matching. The performance of the lognormal distribution is most remarkable in estimating Gini coefficients. It can produce Gini values with as little as 0.02 per cent of absolute errors. For China with a true Gini in the vicinity of 0.4, the technique of Shorrocks and Wan (2006) is expected to yield an estimate of Gini lying in the interval of (0.4003, 0.3997).

In this paper, individual incomes will be converted from quantile information for 29 regions over the period 1988-2001, based on Shorrocks and Wan (2006). For each region/year, a total of 2000 observations will be generated and they are in the format of m non-overlapping groups, with group k containing $m_k = 2000(L(p_{k+1}) - L(p_k))$ observations, where $L(p)$ and p denote income and population shares, respectively. Let y_{ki} ($k = 1, \ldots, m$; $i = 1, \ldots, m_k$) denote the value of the ith observation in class k. The sample mean of class k is given by μ_k, and the corresponding true (reported) mean of class k by μ_k^*.

Assuming a lognormal distribution, the standard deviation of log incomes, σ, can be estimated using:

$$\sigma_k = \Phi^{-1}(p_k) - \Phi^{-1}(L(p_k)) \quad \text{for } k = 1, \ldots, m-1, \tag{6}$$

where Φ is the standard normal distribution function (Aitchison and Brown 1957). After averaging across the m –1 estimates, the raw sample of 2000 observations is generated by the percentile points 0.025, 0.075, …, 99.975 from the fitted lognormal function. These observations, denoted by y, are then adjusted according to the following equations:

$$\hat{y}_j = \mu_k^* + \frac{\mu_{k+1}^* - \mu_k^*}{\mu_{k+1} - \mu_k}(y_j - \mu_k) \qquad \text{for } k = 1, \ldots, m-1 \text{ and } y_j \in [\mu_k, \mu_{k+1}) \tag{7}$$

$$\hat{y}_j = \frac{\mu_1^*}{\mu_1} y_j \quad \text{for } y_j < \mu_1; \quad \hat{y}_j = \frac{\mu_m^*}{\mu_m} y_j \quad \text{for } y_j \geq \mu_k \tag{8}$$

These adjustments are undertaken to ensure that each interval contains its true mean income for those intervals where we have quantile information. However, these adjusted values generally do not possess interval means which exactly match their true mean incomes (i.e., $\mu_k \neq \mu_k^*$). To guarantee precise matching of mean incomes, further transformation is needed to produce

$$y_{ki}^* = c_{k+1} - \frac{c_{k+1} - \mu_k^*}{c_{k+1} - \hat{\mu}_k}(c_{k+1} - \hat{y}_{ki}) \qquad \text{if } \mu_k^* > \hat{\mu}_k \text{ and } k < m \tag{9a}$$

$$y_{ki}^* = c_k + \frac{\mu_k^* - c_k}{\hat{\mu}_k - c_k}(\hat{y}_{ki} - c_k) \qquad \text{if } \mu_k^* < \hat{\mu}_k \text{ or } k = m \tag{9b}$$

where

$$c_1 = 0;\ c_k = \tfrac{1}{2}\left(\max_i \hat{y}_{k-1,i} + \min_i \hat{y}_{ki}\right),\ k > 1$$

These synthetic observations of y^* constitute individual income observation for poverty measurement. Using these samples, we obtain poverty measures, to be discussed in Section 4.

Apart from the income observations, data for other independent variables are sourced from *Comprehensive Statistical Data and Materials for 50 Years of New China* and *China Statistical Yearbook* 2000, 2001, and 2002. These variables include the ratio of trade volume to GDP (*Trade*), ratio of FDI stock to GDP (*FDI*), average years of schooling (*Education*), dependency ratio (*Dependency*), capital stock per capita (*Capital*), proportion of non-agricultural population in total population (*Urbanization*) and proportion of output by state-owned enterprises (SOEs) in total industrial output (*Privatization*). Among these, dependency ratio is calculated as (non-agricultural population-urban employment)/employment, and years of schooling are constructed as in Wan et al. (2007).

4 Poverty decomposition: empirical application

Although any poverty index can be used, we choose to use the squared poverty gap or SPG of Foster et al. (1984) for poverty measurement. The other two commonly used poverty indices—head-count ratio and poverty gap—violate one or both of the monotonicity and transfer axioms. The SPG can be expressed as

$$SPG = \frac{1}{N}\sum_{y_i<z}\left(\frac{z-y_i}{z}\right)^2 \tag{10}$$

where N is the size of population and z is the poverty line.

Until now, no official poverty line has been released for urban China. The PPP-adjusted US$1 and US$2 poverty lines of the World Bank seem too low for urban China although US$2 may be too high for rural China (Wan 2005). Using either of the World Bank's poverty lines adjusted for regional price levels provided by Brandt and Holz (2004), we obtained nil urban poverty for many of the provinces, even in the late 1980s. This is apparently an unrealistic assessment of China's urban poverty and of little research interest. Given the territorial size of and diverse consumption structures in China, it is desirable to use poverty lines that are constructed for individual provinces. One such attempt is made by Hussain (2003) who, using detailed household level expenditure and income data, constructed the 1998 urban poverty lines for all 31 provinces following standard international practice. We choose to use these poverty lines adjusted by regional CPIs.

The calculated SPGs, and Gini estimates as a by-product, are reported in Table 1. Since there are values for 29 regions over 14 years in the sample, presenting estimates for individual provinces and years is more likely to obscure than inform. Hence, only regional averages for the two subperiods of 1988-92 and 1993-2001 are provided. Several interesting points discernable from Table 1 are worth mention. Over time, poverty declined from 1988-92 to 1993-2001 for every region, very much as expected. Across space, most western regions suffer from more severe poverty than their eastern counterparts, a pattern consistent with Fang et al. (2002). Particularly assuring is the relatively high poverty levels in the northeast traditional industrial bases such as Jilin, Heilongjiang and Inner Mongolia.

The Gini estimates all increased over time and do not markedly differ from region to region. The increases are hardly surprising, since rising income inequality has been extensively documented elsewhere. The small differences across regions owe much to the pre-reform egalitarian system which was particularly effective in urban China. The effect of such a system on inequality can be still felt today. Note that the largest Gini value is 28.20 per cent in Table 1, which may appear small to some readers. If the rural-urban divide in China accounts for almost half of a Gini value around 0.4 (Sicular et al. 2007), the Gini for urban China would be less than 0.40. This is because inequality across rural regions is always higher than regional inequality within urban China (Wan 2005). The overall urban Gini can be broken down into a between- and a within- region component. Corresponding to the within-region component, the Gini estimates in Table 1 are quite reasonable. All these points help substantiate the reliability of our synthetic data.

Table 1: Poverty and inequality by region and period

	SPG		Gini	
	1988-92	1993-2001	1988-92	1993-2001
Beijing	0.23	0.02	15.62	20.73
Tianjin	1.10	0.29	17.06	24.98
Hebei	1.65	0.39	13.96	22.41
Shanxi	0.23	0.16	19.50	24.27
Inner Mongolia	1.54	0.38	20.57	24.00
Liaoning	0.15	0.15	15.40	22.47
Jilin	0.81	0.18	18.98	22.75
Heilongjiang	0.73	0.20	18.93	24.24
Shanghai	0.15	0.04	15.78	21.99
Jiangsu	0.16	0.03	16.66	22.94
Zhejiang	0.17	0.02	16.42	22.20
Anhui	0.61	0.10	17.75	21.49
Fujian	4.79	0.03	19.21	22.23
Jiangxi	0.70	0.10	19.23	21.90
Shandong	1.12	0.13	16.35	20.86
Henan	2.82	0.22	21.07	22.56
Hubei	0.21	0.13	17.08	22.22
Hunan	0.28	0.07	18.93	22.99
Guangdong	0.74	0.03	20.58	24.74
Guangxi	1.65	0.18	18.57	22.90
Hainan	1.90	0.46	21.37	26.37
Sichuan	0.25	0.10	18.64	24.31
Guizhou	0.70	0.22	19.63	23.50
Yunnan	0.81	0.10	17.69	21.13
Shaanxi	0.59	0.37	18.90	23.77
Gansu	0.78	0.35	20.36	21.74
Qinghai	0.27	0.09	21.68	23.81
Ningxia	0.71	0.66	19.24	24.52
Xinjiang	1.44	0.39	25.15	28.19

Source: Authors' calculation.

The estimated SPGs are then used to fit regression models for inland regions (Gansu, Qinghai, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Hubei, Hunan, Henan, Guangxi, Sichuan, Guizhou, Yunnan, Shaanxi, Ningxia and Xinjiang) and coastal regions (Beijing, Tianjin, Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Guangdong, Hainan, Shandong and Shanghai) with the following specification:

Ln SPG = f (Gini, Trade, FDI, Education, Dependency, Capital, Urbanization, Privatization, time trend, region dummies).

The dependent variable is the logarithmic form of SPG. Because SPG is always non-negative, assuming a lognormal distribution for SPG is preferable to assuming a normal distribution. In fitting the model for the two regional belts, we split the sample into two subperiods: 1988-92 and 1993-2001. The year 1992 marks the famous tour of southern China by the late Deng Xiaoping. Deng's exhortation for stepping up economic reform during that tour unleashed a series of deregulations, which are believed to have caused significant structural changes in the Chinese economy.

With regard to the inclusion of independent variables, the poverty level at a given poverty line is completely determined by the mean income and the dispersion of income. To control for the dispersion, the Gini index is included as an independent variable. Variables that affect the mean income of a region include per capita capital stock, dependency ratio as a proxy for labor input, average years of schooling as a proxy for human capital, privatization as a proxy for reform/transition status, and province dummies to capture the effects of location and related socioeconomic, environmental or climatic conditions. A time trend is also considered to control for possible technology changes or other time-related effects. Globalization is incorporated by including trade and FDI variables. See the last paragraph in Section 3 for definitions of these variables. It might be argued that the above variables are not strictly exogenous to poverty. For instance, high incidence of poverty might adversely affect the acquisition of human capital. However, such reverse causality, even if significant, is unlikely to be instantaneous. Nonetheless, the education variable is lagged by one year when the models are estimated.

The estimation results are shown in Table 2. Terms associated with region-dummy variables are not reported but are available upon request. These dummy variables are used to capture effects attached to locations such as geographical conditions, culture, local governance, ethnic composition, and so on. We will group all dummy variables and the constant terms and name them 'Other Factors', meaning all determinants other than those explicitly included in the regression function. Since it makes little sense to disentangle the impact and endowment contributions of the 'other factors', they will be lumped together when decomposition results are presented and discussed.

Referring to Table 2, the estimated models seem satisfactory in terms of the signs of parameter estimates and *p*-values. Given the use of panel data, the goodness-of-fit seems acceptable.[3] Most parameters possess signs that are consistent with a priori expectations. In particular, inequality is found to be poverty-increasing and education is poverty-reducing. Interestingly, capital is a significant variable in explaining poverty in coastal China, but highly insignificant in the regression for the inland areas. Conversely, globalization as represented by trade and FDI exerts different effects in different areas and different time periods. It is important to point out that globalization can be a double-edged sword when it comes to poverty reduction. Though generally regarded as growth-enhancing, globalization also brings along risks and changes that the poor may be ill-equipped to cope with. The results in Table 2 are simply yet another piece of evidence against generalization of the globalization–poverty nexus. The positive

[3] The regressions were conducted in STATA using 'xtgls', the feasible GLS estimation facility for fixed-effect panel models. As *R*-square statistics are not available, we report the correlation coefficients of observed and predicted values of the dependent variable, which are labelled as '*r*' in Table 2.

estimates for the urbanization variable in all equations reflect the fact that when farmers become urban inhabitants, which would register an increase in urbanization, they usually are low-income earners in the cities.

Table 2: Regression results of poverty determination by region and period

	1988-92			1993-2001		
Variables	Coefficient	Std error	*p*-value	Coefficient	Std error	*p*-value
			coast			
Gini	0.111	0.070	0.11	0.181	0.032	0.00
Trade	0.009	0.010	0.39	-0.027	0.005	0.00
FDI	3.411	2.350	0.15	2.916	0.693	0.00
Education	-0.126	0.387	0.74	-0.163	0.163	0.32
Dependency	0.297	0.259	0.25	0.562	0.148	0.00
Capital	-0.129	0.037	0.00	-0.127	0.013	0.00
Urbanization	0.059	0.177	0.74	0.197	0.125	0.12
Privatization	-1.613	1.248	0.20	-0.021	0.445	0.96
Trend	-0.712	0.075	0.00	-0.175	0.035	0.00
Constant	1.668	2.095	0.54	-4.097	0.884	0.00
No. of obs.	46			98		
r	0.74			0.50		
			inland			
Gini	0.136	0.026	0.00	0.286	0.026	0.00
Trade	0.006	0.003	0.06	0.003	0.002	0.25
FDI	-0.899	0.513	0.08	-1.612	0.686	0.02
Education	-0.136	0.100	0.18	-0.331	0.096	0.00
Dependency	0.386	0.115	0.00	0.601	0.151	0.00
Capital	-0.011	0.010	0.23	0.001	0.011	0.90
Urbanization	0.161	0.074	0.03	0.039	0.082	0.63
Privatization	-1.039	0.400	0.01	-0.456	0.304	0.13
Trend	-0.330	0.033	0.00	-0.269	0.025	0.00
Constant	-1.391	0.866	0.12	-5.503	0.776	0.00
No. of obs.	76			153		
r	0.71			0.66		

Notes: (1) The dependent variable is the logarithm of squared poverty gap. (2) The education variable is average years of schooling lagged by one year. (3) *r* is the correlation coefficient of the observed and predicted values of logarithmic SPG.

Source: Authors' calculation.

Based on the estimated regression equations, it is fairly straightforward to decompose the poverty differences between the inland and coastal areas according to (5). The decomposition results are presented in Table 3. Consistent with common knowledge, poverty is more severe in inland China as indicated by the negative signs of the total poverty differences in both time periods. The poverty difference became larger in the second period, implying that relative to coastal regions, the inland not only suffered from more severe poverty but also experienced slower progress in the fight against poverty. Another interesting result is that contributions of the ‘other factors’ are positive in both periods. Literally interpreted, it means that the gap of poverty severity between the inland and coastal areas would be even larger if these ‘other factors’ and their effects on poverty were equalized across regions. This is certainly not what policy-makers would like to see or consider. Therefore, the contribution of the ‘other factors’ can be left aside in the following discussions.

Table 3: Decomposition of poverty difference between coastal and inland China

	1988-92		1993-2001	
	Impact	Endowment	Impact	Endowment
Gini	-0.468	-0.266	-2.419	-0.110
Trade	0.060	0.069	-0.729	-0.084
FDI	0.659	0.096	0.761	0.067
Education	0.068	-0.080	1.135	-0.209
Dependency	-0.103	-0.042	-0.039	0.058
Capital	-1.728	-0.044	-1.974	-0.198
Urbanization	-0.299	0.130	0.458	0.138
Privatization	-0.308	0.080	0.219	0.022
Trend	-1.234	0.028	0.470	0.000
Sum	-3.352	-0.029	-2.118	-0.317
Other factors	3.060		1.406	
P	-0.320		-1.027	

Source: Authors’ calculation.

From the third last row of Table 3, it is clear that greater poverty severity in the inland is largely due to differing marginal impacts of poverty determinants, not to differences in endowments. This finding is surprising because the lack of resources has long been conceived as the major cause of such spatial differences in poverty. To be more precise, the overall endowment component, only -0.029 in 1988-92 and -0.317 in 1993-2001, is very small relative to the overall impact component of -3.352 in 1988-92 and -2.118 in 1993-2001. Consequently, eliminating differences in resource endowment between the inland and the coast would only yield negligible impact on the coast-inland poverty difference. What is really important is to enhance the poverty-reducing impacts of various factors in the inland regions.

Among the variables included in the model, capital stock per capita is by far the most important factor in determining poverty severity. Although capital is poverty-reducing in both the inland and the coast (see Table 2), it is much more effective in coastal China. The difference in this effectiveness accounts for more than half of the total impact components in both periods. The second most important factor is inequality, with negative impact and endowment effects in both periods. Hence, although inequality is poverty-increasing in both areas (see Table 2), its negative endowment and impact components indicate that the average level of inequality and its marginal impact on poverty severity are both greater in the inland. Strictly speaking, the time trend variable should yield a nil endowment contribution if the panel data are balanced. This is the case for the second period, but not the first period. Numerical results associated with variables other than the time trend, capital and the first three variables of Table 3 can be interpreted analogously, but they appear less important as far as reducing poverty severity in the inland area relative to the coast is concerned.

What role did globalization play in this context? In the first period of 1988-1992, both trade and FDI helped to narrow the poverty difference. In the second period, FDI maintained its positive contributions. However, trade became a factor helping to enlarge the poverty-difference in the second period. This is because trade was anti-poor in the first period but became a poverty-reducing factor in the second period for the coastal regions (see Table 2). For the inland regions, however, trade remained a poverty-increasing variable in both periods. In fact, if one looks into finer components, many of them changed signs from the first period to the second period. Although beyond the scope of this paper, it would be interesting to explore the causes of these changes in sign.

5 Summary

Persistent differences in poverty across locations, quite common in reality, constitute a constant strain on social cohesion. Understanding the causes of such differences is the first step in tackling this spatial-imbalance problem. Even where the causes are known to lies in resource endowments, policy-making may still require some indications as to which resources are more important than the others. We believe that the poverty decomposition framework developed in this paper, which provides a way of quantifying the contributions of poverty determinants to poverty differences across space, will prove a useful tool in this regard. In fact, the applicability of the proposed framework is not limited to spatial poverty differences. It can also be used to analyze poverty variations over time or between population subgroups.

In order to estimate poverty indices from grouped income data, the procedure of Shorrocks and Wan (2006) is introduced for generating individual income records from quantile information. Researchers, particularly those working on poverty and inequality issues in developing countries, may find this procedure useful as they often face financial or other constraints in accessing unit-record data. As one only needs to assume a lognormal distribution, the procedure should be easy to implement in any statistical or econometric packages.

As an illustration, the data-generating procedure and the decomposition framework are applied to exploring why poverty is more severe in inland than in coastal China. It is found that not only do the impacts of trade and FDI on poverty not always agree, they also tend to vary across locations and over time. As dramatically increased trade and FDI inflows are the two most poignant aspects of China's integration into the world economy, these findings provide some insights into the much debated question of whether globalization brings poverty or prosperity. The first point to note is that globalization is a multi-faceted process. Evidence on any single aspect of globalization, be it trade, FDI or integrated financial markets, does not usually suffice for drawing conclusions about the causality between poverty and globalization. Doing so risks not seeing the wood for the trees, as the differing effects of trade and FDI in this paper show. The spatial and temporal variability of the effects of trade and FDI demonstrates the potential pitfalls of generalizing the experiences of specific places or periods. Globalization works along and interacts with other determinants of poverty. The various forces are more likely to be in flux in an open economy than in a closed economy. The challenge for policy-makers is, therefore, to keep close tabs on the circumstances on the ground and adapt their policies accordingly to ensure that globalization serves the poor.

It is also found that, depending on the time period considered, domestic capital or inequality was the most important contributor to the poverty difference. This suggests that while the central government should continue to support the poor western regions in accumulating capital, the main responsibility rests with individual regional governments. They must improve the effectiveness of capital input on poverty reduction and must divert some attention to the issue of inequality within each region, which has so far been largely neglected in China.

Finally, our results show that a variable may be statistically insignificant in explaining poverty yet still contribute substantially to total poverty difference. This finding calls for caution against dropping some insignificant variables from regression equations.

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