Geographic Inequity in a Decentralized Anti-Poverty Program:

A Case Study of China

Martin Ravallion

The World Bank
Development Research Group
Poverty Team
August 2007

Abstract

The central governments of many developing countries have chosen to decentralize their anti-poverty programs, in the expectation that local agents are better informed about local needs. The paper shows that this potential advantage of decentralized eligibility criteria can come at a large cost, to the extent that the induced geographic inequities undermine performance in reaching the income- poor nationally. These issues are studied

empirically for (probably) the largest transfer-based poverty program in the world, namely China's Di Bao program, which aims to assure a minimum income through means-tested transfers. Poor municipalities are found to adopt systematically lower eligibility thresholds, reducing the program's ability to reach poor areas, and generating considerable horizontal inequity.

This paper—a product of the Development Research Group, is part of a larger effort in the department to assess the performance of anti-poverty programs in developing countries. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The author may be contacted at mravallion@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

Geographic Inequity in a Decentralized Anti-Poverty Program: A Case Study of China

Martin Ravallion¹

*Development Research Group, World Bank
1818 H Street NW, Washington DC, 20433*

Keywords: Cash transfers, fiscal decentralization, poverty lines, targeting, China

JEL: H70, I32, I38, O18

¹ The findings, interpretations and conclusions of this paper are those of the author and should not be attributed to the World Bank or any affiliated organization. The author is grateful for the assistance of Shaohua Chen and Youjuan Wang in setting up the data set used here. The paper has also benefited from useful discussions with Philip O’Keefe and staff of the Ministry of Civil Affairs and the National Bureau of Statistics, Government of China. Helpful comments on this paper were received from Bert Hofman, Stuti Khemani, Phillippe Leite, Ghazala Mansuri, Vijayendra Rao, Dominique van de Walle and Xiaoqing Yu.

1. Introduction

The public finance literature recommends that redistributive transfers aiming to reduce poverty should be the responsibility of the central government in a federal system.² The main argument against decentralizing such programs is that doing so will induce migration responses, which will be costly and undermine the redistributive effort.³

This policy recommendation is conspicuously not being followed in many developing countries. It is now quite common for central governments to decentralize key aspects of the implementation and funding of their anti-poverty programs. Typically the center continues to provide broad guidelines and at least partial co-funding, but is relieved of the need to decide on the specific beneficiaries of that funding. Information asymmetries in developing countries have been the main justification for such decentralized redistributive policies. Advocates argue that local agents are better informed than the center about local conditions for the purpose of assessing eligibility. These information problems are believed to have special salience in developing countries. However, the recent literature has also pointed out that the same information problems create prospects for capture by local elites, subverting the center's aims.⁴

Another important stylized fact about developing countries is the large geographic disparities one observes. As this paper will argue, these disparities can be associated with perverse geographic inequities in the outcomes of a decentralized anti-poverty program; indeed, it is quite possible to find that the induced inter-jurisdictional disparities in program spending far exceed the (large) disparities in mean incomes. Then, under certain conditions, decentralization can severely limit the scope for reducing absolute poverty when judged by consistent national criteria. The gains to the center in devolving power over beneficiary selection to local agents may come at a high price in terms of the program's overall impact on poverty.

The essence of the problem is that local agents, who must typically commit at least some resources to the program, need not share the center's goals. Their budget-constrained choices can then undermine the program's performance against poverty nationally. For certain preferences of local agents, the government of a poor area will deliberately understate its

² The classic exposition is Oates (1972), although also see the more qualified view in Oates (1992).

³ For example, Feldstein and Wrobel (1998) argue that state government efforts at redistribution in the US have been largely unsuccessful, and that the mobility across state boundaries is the main reason.

⁴ On the arguments and evidence for and against decentralization of anti-poverty programs in developing countries see Bardhan and Mookherjee (2000), Alderman (2002), Bardhan (2002), Mansuri and Rao (2004) and Galasso and Ravallion (2005).

poverty, as an adaptation to its budget constraint. Geographic inequity arises in that poor areas spend less on their poor. Horizontal inequity also emerges, in that equally-poor people are treated differently depending on where they live.

Such concerns are not new. In the past they have been seen to yield a compelling equity case for central action, aiming to assure that *ex ante* equals are treated equally by the fiscal system (as advocated by Buchanan, 1950). The idea is that the center should correct for the inequities by differential cost-sharing or intergovernmental transfers.⁵ However, the extent to which such corrective policies are feasible in practice remains a moot point, given the very same information asymmetries that have motivated the decentralization of anti-poverty programs. Indeed, as this paper will show, the information needed to eliminate the bias against poor areas *ex post* is even more demanding than that needed to directly implement the center's preferred program. And the fact that poor areas tend to have poor services in so many developing countries is hardly suggestive of strong geographic redistribution of spending and fiscal burdens.⁶ Political influence on the outcomes can also be expected, and it would not be too surprising if this favored better-off areas.⁷ The case for believing that cost-sharing or transfers can solve the problem is far from obvious.

The paper studies these issues in the context of a specific type of anti-poverty program in which means-tested transfers aim to bring everyone up to an assured minimum income. The theoretical characterization in the following section demonstrates just how much decentralized beneficiary selection can reduce the overall poverty impact of such a program when impact is judged by consistent national criteria. In one example, a central budget sufficient to eliminate poverty leaves 90% of the problem untouched when program implementation is decentralized under a fixed cost-sharing rule; this holds even with perfect targeting (according to local eligibility criteria) within all jurisdictions. Furthermore, in this model, the vertical and horizontal inequities come hand-in-hand; the only way to assure equal treatment of *ex ante* equals is to eliminate the inequality in provision between rich and poor areas.

⁵ See McLure's (1995) comments on Prud'homme (1995). Boadway (2003) provides a good overview of this topic.

⁶ In the context of China, the redistributive impact of the existing system of intergovernmental transfers is known to be quite weak; see Tsui (2005), Shen et al. (2006) and Shah and Shen (2006).

⁷ For a review of the literature on political influences on intergovernmental transfers for the purpose of regional equalization see Khemani (2006).

The rest of the paper provides a case study for a concrete example of this type of program. In an effort to redress China's sharply rising income inequality and signs of weak social protection for vulnerable groups, the central government recently introduced the *Di Bao* program, which aims to bring everyone up to an acceptable minimum income. Initially the program is only available to urban areas, but it is intended to expand it to national coverage. Like many areas of social spending in China, *Di Bao* relies on decentralized implementation.⁸

Section 3 describes the *Di Bao* program in greater detail and describes the data used in this study, covering China's 35 largest cities. Section 4 explores the inter-city differences in spending and other program parameters. The main finding is that poorer municipalities tend to set less generous eligibility criteria, which greatly attenuates, but does not eliminate, the program's efficacy in reaching poor areas. Section 5 tests for horizontal inequity, using micro data, and finds large inter-city differences in the probability of participation at given (observable) household characteristics. Section 6 concludes.

2. Geographic inequity in a stylized anti-poverty program

The following model is a stylized version of the type of scheme that will be studied empirically. While it is a contextual model, the analysis will point to some generic issues, likely to be shared by other schemes. The model deliberately abstracts from the problems of mobility and distribution within local jurisdictions that have been emphasized in the literature, so as to focus on the inter-jurisdictional and associated horizontal inequities.

It is assumed that the central government's aim for the program is to provide cash transfers sufficient to bring everyone in municipality j ($=1, \dots, n$) up to an income level Z_j^* , sufficient to not be deemed "poor" in that municipality. These poverty lines may be either absolute (constant real value across municipalities) or relative (rising with mean income of the municipality). The resulting public expenditure will be distributed across municipalities such that the higher their poverty gap, the higher their spending allocation. Spending on municipality j ($=1, \dots, n$) with income distribution $F_j(y)$ is:

⁸ Concerns have been voiced about the implications of China's high level of fiscal decentralization for the country's poor areas; see, among others, West and Wong (1995), Park et al., (1996), Kanbur and Zhang (2005), Shen et al. (2006) and Zhang (2006).

$$C_j^* = \int_0^{Z_j^*} (Z_j^* - y) dF_j(y) = (Z_j^* - \bar{Y}_j^{Z^*}) H_j^* \quad (1)$$

where $H_j^* \equiv F_j(Z_j^*)(> 0)$ is the poverty rate (“headcount index”) and $\bar{Y}_j^{Z^*}$ is the mean income of the poor when the poverty line is Z_j^* . The cost of the program is implicitly a function of all parameters of the distribution function, $F_j(y)$. These include the mean, $\bar{Y}_j$, and the distribution of incomes relative to the mean, which is taken to be fully described by a vector of parameters L_j . C_j^* is also a function of Z_j^* at a given $F_j(y)$. It is convenient to re-write (1) as:

$$C_j^* = C(\bar{Y}_j, L_j, Z_j^*) \quad (2)$$

The center does not have the information needed to implement this program. It has access to a national sample survey that includes household incomes or expenditures but it can only observe the nominal distribution of income in those provinces or municipalities for which the survey has sufficient sample size to be considered representative. However, it is implausible that most national surveys would be representative at the levels of government at which one would probably want to implement such a program, to exploit local information for assigning eligibility. And there are differences across municipalities in the cost-of-living and other sources of heterogeneity in the money needed to achieve a given level of welfare — differences that are unobserved by the center. For example, it is still quite rare to have spatial cost-of-living indices in developing countries (although this is changing). Additionally, there are likely to be idiosyncratic differences in needs (even without price differences). Climate and the existence other public programs are examples.

Decentralized implementation entails that the center gives each municipality the power to select beneficiaries, but requires co-financing to help control the program. Local agents fill the poverty gaps but are free to determine the local poverty line. Total spending on the program in municipality j is given by $C(\bar{Y}_j, L_j, Z_j)$ where Z_j is the municipality’s chosen poverty line. I shall close off the possibility of re-location in response to the variation in Z_j across municipalities. This can be rationalized by either the prohibitive costs of moving or residency requirements (whereby only long-standing residents are entitled to the program).

How will local spending vary with mean income? Intuitively, we might expect two effects, working in opposite directions. Municipalities with lower mean incomes will tend to

have higher poverty; call this the “needs effect.” At the same time, a poorer municipality will have fewer resources for fighting poverty — the “resources effect”. However, this intuition ignores two confounding factors: shifts in the (relative) distribution and the preferences of local agents. To see this more clearly, differentiating w.r.t. the mean, as follows:

$$\frac{dC(\bar{Y}_j, L_j, Z_j)}{d\bar{Y}_j} = \left[\frac{dC(\bar{Y}_j, L_j, Z_j)}{d\bar{Y}_j} \right]_{Z=const.} + H_j \frac{\partial Z_j}{\partial \bar{Y}_j} \quad (3)$$

where $H_j = F_j(Z_j)$. The first term on the RHS is the needs effect and the second is the resources effect. The needs effect can be broken down as:

$$\left[\frac{dC(\bar{Y}_j, Z_j, L_j)}{d\bar{Y}_j} \right]_{Z=const.} = -\omega_j + \frac{\partial C}{\partial L_j} \cdot \frac{dL_j}{d\bar{Y}_j} \quad (4)$$

where $\omega_j \equiv H_j \bar{Y}_j^Z / \bar{Y}_j$ ($0 < \omega_j < 1$) is the income share of the poor.⁹ The first term is unambiguously negative but the second term — the distributional effect given by the product of the two gradient vectors, $\partial C / \partial L_j$ and $dL_j / d\bar{Y}_j$ — could have either sign. I will say that the expansion path for spending is “distribution neutral” if this distributional effect is zero.

The direction and size of the resources effect depends on the scheme’s design and the behavior of local agents. A key design feature is that the center sets the share of the program cost to be financed locally; that share is denoted α_j , where $0 < \alpha_j \leq 1$ for all j . The center chooses α_j to assure that the central budget is not exceeded. (The differential cost shares can also be chosen to help control local choices, as discussed later.) Income of the municipality net of spending on the program is $\bar{Y}_j - \alpha_j C_j$, where $\bar{Y}_j$ is gross income. The program’s local income share is $s_j \equiv \alpha_j C_j / \bar{Y}_j$.

In characterizing the behavior of local agents, it can be presumed that they do not care solely about reducing poverty, which they must balance against the burden of co-financing. It is assumed that each municipality has preferences over spending on the program and other uses of

⁹ To verify (4) note that $C = \int_0^H (Z - y(p))dp$ where $y(p)$ is the quantile function (inverse of the distribution function, $p=F(y)$). Then $\frac{\partial C}{\partial \bar{Y}} = -\int_0^H \frac{\partial y(p)}{\partial \bar{Y}} dp = -\omega$ on noting that $\frac{\bar{Y}}{y(p)} \cdot \frac{\partial y(p)}{\partial \bar{Y}} = 1$ given that the partial derivative holds L constant.

local income, both valued positively. In rationalizing the assumption that the local authorities value spending on poverty reduction, we can either imagine that they care intrinsically about their impact on poverty or that it is seen to be instrumentally important. The latter case rests on the fact that the program attracts resources from the center, given the co-financing feature. Reaching a larger slice of the local population through the anti-poverty program may well buttress the position of local authorities, making it more likely that they stay in power.¹⁰ It is assumed that the program's local impact on poverty is measured by the poverty gap.

Since the local agents care about other uses of resources besides spending on the poverty-reduction program, one can immediately see that geographic inequity arises as long as program spending is a “normal good” (i.e., with a positive income effect). To formalize this intuition and explore the conditions required, let us assume that each municipality has a preference ordering over the two “goods”: local spending on the program and income net of local program spending. Let the preferences be represented by a welfare function:

$$W_j = W(\bar{Y}_j - \alpha_j C_j, C_j) \quad (5)$$

The function W is assumed to be strictly increasing in both arguments. The conditions for an optimum with respect to C_j (or, equivalently, Z_j) are that:¹¹

$$\alpha_j W_Y(\bar{Y}_j - \alpha_j C_j, C_j) = W_C(\bar{Y}_j - \alpha_j C_j, C_j) \quad (6.1)$$

$$\alpha_j^2 W_{YY} - 2\alpha_j W_{YC} + W_{CC} < 0 \quad (6.2)$$

(Subscripts on W denote partial derivatives.) Implicitly differentiating (6.1) with respect to $\bar{Y}_j$:

$$\frac{dC_j}{d\bar{Y}_j} = \frac{\alpha_j W_{YY} - W_{YC}}{\alpha_j^2 W_{YY} - 2\alpha_j W_{YC} + W_{CC}} \quad (7)$$

The direction of the municipal income effect is ambiguous, under the assumptions made so far.

To help interpret equation (7), let us consider four special cases.

¹⁰ It is not only in a democracy that public authorities gain from such behavior. A city government in China that was widely seen to neglect its local population would be unlikely to stay in power very long.

¹¹ The problem is formally identical to a model of consumer behavior in which α is interpretable as the relative price of spending on the poverty-reduction program. Without the co-financing requirement the municipality will choose a corner solution in which all its residents are deemed to be “poor.”

Case 1: Suppose that higher municipal income lowers the marginal welfare of program ($W_{YC} < 0$) and that the municipality's objective is linear in income ($W_{YY} = 0$).¹² Then it is immediate from (7) that $dC_j / d\bar{Y}_j < 0$; poorer cities will spend more on the program.

Case 2: Suppose instead that $W(\cdot)$ is separable between the two types of spending ($W_{YC} = 0$) and has strictly diminishing returns to income ($W_{YY} < 0$). (Separability can be weakened to $W_{YC} > \alpha_j W_{YY}$.) Then $dC_j / d\bar{Y}_j > 0$; poorer cities will spend less on the program, in marked contrast to the centralized program.

Case 3: Now add to Case 2 the assumption of linearity in spending on poverty ($W_{CC} = 0$). Then the income effect on spending is simply the inverse co-financing share:

$$\frac{dC_j}{d\bar{Y}_j} = \frac{1}{\alpha_j} \geq 1 \quad (8)$$

Not only will the resources effect dominate, but the total income effect will be no less than unity. At a 50% cost share (say), spending on the program will rise by \$2 for each \$1 gain in mean municipal income. Furthermore, local spending on the program will be quite income elastic; the income elasticity is simply the inverse of the share of local income devoted to the program (s_j).

Table 1 gives a numerical example. There are two regions, one “poor,” one “rich.” Incomes are normalized by the center's poverty lines, Z_j^* ($j=1, \dots, n$), relative to some reference value, so only a single real poverty line is needed. Given the parameter values in Table 1, filling the poverty gaps, when assessed by a single national (real) poverty line, would require \$10 per capita in the rich region and \$135 in the poor region. 90% of the national poverty gap (the population-weighted aggregate of $(Z^* - \bar{Y}_j^Z)H_j$ across the two regions) is in the poor region. Under the “Case 3” welfare function $400 \ln(\bar{Y}_j - 0.5C_j) + C_j$ (with a 50% cost share), the decentralized version of the program (at the same cost to the center) will entail that all the program's budget goes to the rich region, with none to the poor region. Instead of eliminating poverty, as judged by the national poverty line, the decentralized program will leave 90% of the problem untouched, even with perfect targeting.

¹² This case also requires sufficiently strongly diminishing returns to spending ($W_{CC} < 2\alpha W_{YC}$).

Case 4: A further insight into just how powerful the resources constraint can be is obtained if we combine Case 3 with the assumption of distribution neutrality ($dL_j / d\bar{Y}_j = 0$).

Then one obtains strikingly simple formulae for the decomposition in equation (3):

$$\left[\frac{\partial C_j}{\partial \bar{Y}_j} \right]_{Z=\text{const.}} = -\omega_j < 0 \text{ (the needs effect)} \quad (9.1)$$

$$H_j \frac{\partial Z_j}{\partial \bar{Y}_j} = \frac{1}{\alpha_j} + \omega_j > 0 \text{ (the resources effect)} \quad (9.2)$$

This suggests that differences in needs may well play a very modest role under Case 4. In a municipality with the typical amount of income inequality and a medium size program, ω_j will be quite small — unlikely to exceed 0.05. With a 50% cost-share, the resources effect will be 2.05, utterly swamping the needs effect.

A further implication of the existence of a municipal income effect on the poverty line is that the decentralized program will generate horizontal inequity — heterogeneous gains among people who are identical *ex ante*. This happens in two ways. Firstly, when the income effect on the poverty line is positive there will be people living in poor municipalities who are left out of the program, but would be covered if they lived in a sufficiently better-off area. This stems from the region of non-overlapping support (in the income dimension) induced by the income gradient of the poverty line. Secondly, participants within the region of common support who are at the same pre-intervention income will have different poverty gaps and (hence) receive different transfers, depending on where they live.

Can such geographic inequities (both vertical and horizontal) be redressed by a differential cost-sharing arrangement? To see what would be required, note that Z_j satisfying equation (6.1) can be written as: $Z_j = Z_j(\bar{Y}_j, \alpha_j)$. Consider the conditional cost share, $\alpha_j^* = \alpha_j^*(\bar{Y}_j, Z_j^*)$, defined implicitly by $Z_j^* = Z_j(\bar{Y}_j, \alpha_j^*)$. If the center sets α_j^* then it will assure that, under decentralization, each municipality chooses the national poverty line, Z_j^* . (In the numerical example in Table 1, local cost shares of 0.37 and 0.73 for the poor and rich regions, respectively, will induce them to choose the center's preferred spending levels under

decentralization.) Note that when the center has set the cost shares $\alpha_j^*, j=1, \dots, n$, there will only a municipal income effect on the poverty lines if the center's poverty lines vary with mean income.

However, the data requirements for such a cost-sharing formula are far from innocuous. The function $Z_j(\bar{Y}_j, \alpha_j^*)$ varies across jurisdictions according to the distribution of income as well as any idiosyncratic factors in preferences. Indeed, with less information than is needed to work out the α_j^* 's, the center could impose its ideal program at local level. The cost-sharing arrangements found in practice may be subject to severe information and computational constraints on the extent to which the biases against poor areas can in fact be eliminated.

The rest of this paper will explore the above issues in the context of a specific program, with the same design features as that discussed above.

3. Setting and data

China's old safety-net provided by guaranteed employment and enterprise-based benefits has largely disappeared, leaving some households vulnerable. These may have been adversely affected by economic change or been unable to participate in the new economic opportunities due to their lack of skills, long-term illness or disability. Some of the "left behind" households started poor and some became poor, even though aggregate poverty rates have tended to fall over time.¹³ Urban areas have figured prominently in these concerns about the "new poor."

The *Di Bao* (DB) program has been the central government's main response to these new challenges for social protection. The program aims to provide a transfer to all registered urban households with incomes below a DB poverty line.¹⁴ The aim is to close the gap between the recipient's income and the DB line, so that a minimum income is guaranteed.

Di Bao is one of a number of central programs in China that are scaled-up versions of programs that started in just one locality. (This is another aspect of decentralization in China, namely the use local-level policy experiments, some of which are deemed successful and then go national.) The DB program started in Shanghai in 1993, where it was deemed to be a success and so became a national policy with formal regulations issued by the State Council in 1999.

¹³ On China's record against absolute poverty since the current period of reforms began around 1980 see Ravallion and Chen (2007).

¹⁴ "Registered" urban residents are those with an official registration for urban residence. There are also non-registered urban residents, who are often recent migrants from rural areas.

The program then expanded rapidly and by 2003 participation had leveled off at 22 million people per year over 2003-05, representing 6% of urban residents, at a cost of about 0.1% of GDP. It is administered by the Ministry of Civil Affairs (MoCA).

The program's implementation is heavily decentralized. While the national and provincial governments provide guidelines and co-financing, the selection of beneficiaries and program implementation are under municipal control. Individual municipalities determine their DB line and finance the transfers in part from local resources. The center provides only very general guidance on how DB lines are to be set. References are made in the regulations to the need to assure that basic consumption needs are met, though mention is also made of the need to take account of local socio-economic conditions (possibly interpretable as "relative poverty" considerations) and local fiscal constraints (O'Keefe, 2004; World Bank, 2007).

The fact that local authorities retained power over the DB cut-off points for eligibility undoubtedly reflects the center's lack of information available on differences in the cost of basic needs in different cities, and also differences in what those "basic needs" entail. However, it appears likely that the center also felt that there were limits to how much it could credibly control the local authorities, even with good information. The history of the program — notably the fact that DB had emerged from the local level — might also have influenced the extent of decentralization in implementing the scaled-up national version of the program.

Applicants for DB are screened locally to assure that their income is below the relevant DB line. Claimants apply to their local residential committee, which administers the program on a day-to-day basis, though the formal decision is made by the local (county-level) Civil Affairs office. There is also a community vetting process whereby the list of proposed participants is displayed on notice boards and community members are encouraged to identify any undeserving applicants.¹⁵ MOCA officials (in interviews with the author) acknowledge that the advantage of involving local community groups in this process is their greater knowledge of local conditions.

Cofinancing is available to most provinces from the center. In 2003-04, about 60% of the cost was financed by the central government. This share varies across provinces, although it is not clear how the cost shares are determined by the center. A State Council Circular from 2000

¹⁵ This raises concerns about stigma effects. World Bank (2007) reports results of a survey of DB participants in Liaoning province, which found that only 10 percent were ashamed or uncomfortable with disclosure of their household information in the application process. However, there may well be a selection bias in this calculation, if those deterred by public disclosure chose not to participate in DB.

says that “...central finance will render support to areas with financial difficulties at its discretion.”; a further 2001 State Council circular clarifies that central funding was available for provinces with financial difficulties, in light of their specific financial strength and *Di Bao* demand.¹⁶ World Bank (2007, p.11) reports that “...the share of central financing relative to in-province financing for 2002 ranged from zero in coastal provinces to 100 percent in Tibet, and 88 percent in Ningxia.” This is suggestive of an effort to set higher central cost shares in poorer provinces. However, in the context of public spending generally, it is also known that the terms of intergovernmental transfers are subject to a process of political negotiation that is not seen to typically favor poorer provinces (Shen et al., 2006). It would be surprising if the DB program were immune to these political effects.

The present empirical analysis is based on two data sources. The first is the available set of (both published and unpublished) administrative records for the program. Most importantly, the administrative records provided the data on the local poverty lines, which could be mapped to the city-level for the largest 35 municipalities, which are the setting for this study.

The second data source is China’s Urban Household Short Survey (UHSS) for 2003/04. UHSS was done by the Urban Household Survey Division of the National Bureau of Statistics (NBS) as a first step in constructing the sample for the regular Urban Household Survey (UHS), which has a much longer questionnaire, but much smaller sample size. This paper uses the UHSS sample for the 35 largest cities, giving a total sample of 76,000 households. The big advantage of the UHSS over alternative survey data sets in this context is that its large sample size allows it to be representative at the level of each of the 35 largest cities; the sample sizes vary from 450 (in Shenzhen) to 12,000 (in Beijing). Thus one can expect to be able to make reasonably reliable inter-city comparisons, though (of course) sampling and non-sampling errors must still be expected. For the 35 cities with adequate sample sizes, the definitions of geographic areas in the UHSS also coincide exactly with those for the DB lines.¹⁷ The entire data set has been cleaned by NBS staff and made available for this research. While the UHSS is a relatively short survey, it allows us to measure a fairly wide range of household characteristics including income. Chen et al. (2006) describe the survey data in greater detail. Table 2 gives

¹⁶ This information is from correspondence with Philip O’Keefe at the World Bank.

¹⁷ Outside these 35 cities, the local DB lines are not coded or use different codes, and in many cases use different boundaries to the geographic areas used by UHSS; a further problem is that the bulk of the UHSS data outside the 35 cities has not been cleaned.

summary statistics by city. Note that UHSS did not exist in time for using it in the design of the DB program. In particular, DB lines had been set prior to the survey.

Two data problems are notable. Firstly, the survey measured household income from responses to the single question “What is your household’s total income?” (However respondents were also asked how much of their income comes from wages.) Responses to this question are unlikely to give as accurate a measure of income as obtained from surveys that base the income aggregates on many detailed questions, such as NBS’s UHS, although this survey is too small for city-level analysis. To some extent, the measurement errors will average out at city level, but errors are still to be expected. I will note some implications of this problem along the way.

Secondly, there is no municipal cost-of-living index for China. The DB lines may well reflect (at least in part) cost-of-living differences. I will discuss the likely biases due to this problem, and argue that the main results are robust.

Chen et al. (2006) use the UHSS data to assess the program’s targeting performance and impacts on poverty. Various measures indicate that its targeting performance — as defined by the program’s ability to concentrate benefits among the poor by avoiding leakage to the non-poor — is excellent by international standards. Coady et al. (2004) compile a measure of targeting performance for 122 programs across 48 developing countries; their measure is the share of spending going to the poorest $x\%$ divided by x . (so that a uniform allocation, independent of income, gets a value of unity). The median of this measure across the 122 programs is 1.25. The highest value is 4.0 (for Argentina’s *Trabajar* program). By contrast, the value estimated by Chen et al., for the DB program is 8.3, making it a better performer by this measure than all the programs surveyed by Coady et al. (2004).

Nonetheless, the overall impact on poverty appears to be modest. In the same sample, Chen et al., find that the poverty gap index (C_j / Z_j), based on income net of DB receipts, is 2.28%; on adding in DB payments it only falls to 2.06%. (Among participants only, the corresponding figures are 19.92% and 14.23%; the higher index for participants reflects the programs’ targeting to the poor.) This largely reflects weak coverage of the poor, as identified by the UHSS.¹⁸ Performance improves if one allows for measurement errors in the UHSS, and

¹⁸ This echoes observations from some of the literature on targeting in developing countries that has pointed to the inadequacies of focusing solely on the problem of avoiding leakage to the non-poor, largely ignoring the dual problem of incomplete coverage. In particular, see Cornia and Stewart (1995) who

inconsistencies between the UHSS definition of “income” and that used by the local authorities in charge of the program (Ravallion, 2007).

4. Cross-city evidence for the *Di Bao* program

The model in section 2 showed that the income effect on program spending is the net outcome of two opposing effects, the needs effect (whereby poorer municipalities have a greater poverty problem to be addressed) and the resources effect (whereby poorer municipalities have fewer resources for covering their share of the cost). The relative strength of these two effects depends on design features of the program and the objectives of local agents. In addition, there are likely to be other sources of municipal income effects on the program, such as differences in administrative capabilities, which may well be income dependent.

In the theoretical model, program spending has a precise mathematical relationship to the poverty line and income distribution, as given by equation (1). However, as noted in section 3, the DB program does not appear to operate in practice exactly the way its design intends. This fact, and measurement errors, create imprecision in the relationship. I assume that actual DB spending (S) is related to the theoretical level of spending defined by equation (2) as:

$$\ln S_j = \ln C(\bar{Y}_j, L_j, Z_j) + \varepsilon_j \quad (10)$$

where ε_j is a standard white noise error term (I will comment on some concerns with this assumption along the way). The DB poverty line (Z) is in turn a function of the mean (and L), through the municipal choice of eligibility. In principle, one might also allow the parameters of the relative distribution to vary with the mean, though I do not model this explicitly.

Let us first consider the reduced form relationship between program spending and mean income. Across the 35 cities, the regression coefficient of log DB spending per capita on log mean income is -0.220, but it is not significantly different from zero ($t=-0.66$).¹⁹ Figure 1 plots the data. (The correlation coefficient is -0.098.) If one drops the richest city, Shenzhen, then the estimated income elasticity falls to -0.150 ($t=-0.31$). There is also a strong positive income effect on DB expenditure per DB recipient, which has an elasticity of about unity to city income; the

argue that there has been excessive emphasis in policy discussions on “type 1 errors of targeting” (incorrectly classifying a person as poor) relative to “type 2 errors” (incorrectly classifying a person as not poor). Naturally, the impact on a standard measure of poverty reflects both.

¹⁹

All t-ratios in this paper are based on White standard errors, corrected for heteroscedasticity.

regression coefficient of the log DB payment per recipient on log mean income of the city is 0.977 (t=5.18). Figure 2 plots the data on spending per recipient.

Note that mean income includes DB payments, creating an endogeneity concern. Using mean income net of DB payments does not eliminate endogeneity concerns (given possible behavioral responses to the program), but it is, nonetheless, reassuring that doing so gives a virtually identical result (a regression coefficient of spending on net income of -0.226; t=-0.68). Other results reported below were similarly robust to using net income instead of total income.

Let us turn now to the structural form model in (11). To allow for distributional effects I used the standard deviation of incomes within each municipality.²⁰ I initially used a cubic in log Z , but the higher-order terms were individually and jointly insignificant (prob. values around 0.5), so I opted for the following regression of log spending per capita (S) on both log mean income, the standard deviation (SD) and the log DB line:

$$\ln S_i = 9.443 - 2.386 \ln \bar{Y}_i + 0.113 SD_i + 1.720 \ln Z_i + \hat{\varepsilon}_i \quad R^2=0.147; n=35 \quad (11)$$

(1.58) (-2.63) (2.15) (2.42)

Here we see clearly both the needs effect (a lower mean income and more unequal distribution generate higher spending at a given DB line) and resources effect (through the choice of the DB line).²¹ (Equation (11) changed very little on dropping Shenzhen.)

The total income elasticity of spending is the outcome of three effects, a direct income effect, an effect via the standard deviation of incomes and an effect via the DB line. Grouping the former two channels together as the needs effect, it is also of interest to estimate the “partial reduced form” regression of spending on just mean income and the DB line, giving:

$$\ln S_i = -0.468 - 0.925 \ln \bar{Y}_i + 1.401 \ln Z_i + \hat{\varepsilon}_i \quad R^2=0.075; n=35 \quad (12)$$

(-0.13) (1.89) (2.06)

On estimating a similar specification to (11) for log DB payments per recipient (S/P , where P is the DB participation rate) the standard deviation was statistically insignificant (t=0.27), so I dropped it giving:

$$\ln(S_i / P_i) = -6.571 + 0.488 \ln \bar{Y}_i + 0.971 \ln Z_i + \hat{\varepsilon}_i \quad R^2=0.568; n=35 \quad (13)$$

(-3.59) (2.46) (3.43)

²⁰ With only 35 observations, there are limits to how many distributional parameters one can allow for. I also tried the coefficient of variation as an alternative, but the standard deviation was preferred in terms of goodness of fit.

²¹ The causal interpretation of this regression is questionable given that the DB line is jointly determined with program spending. Nor is there any valid instrumental variable, given that anything that influenced the DB line would presumably also influence spending conditional on the DB line. However, the aim here is only test for a conditional income effect, at a given DB line.

Notice that the income effect has switched sign in going from (12) to (13). This clearly stems from a negative income effect on DB participation. The estimated elasticity of the DB participation rate to mean income is -1.197 (with a t-ratio of -3.85). Figure 3 plots the relationship found in the data. The elasticity is even higher (in absolute value) if one controls for the DB poverty line; the income elasticity of participation then rises to -1.413 (t=-3.31).

There is a strong positive income effect on the DB line. The regression coefficient of the log DB line on log mean income is 0.503, which is significantly different from zero at the 1% level (t=6.92) but also significantly less than unity (t=6.84). Figure 4 gives the scatter plot.²² Dropping Shenzhen, the estimated income elasticity of the DB line is 0.579 (t=8.36).

Thus the small total income effect on spending is the outcome of a negative income effect at given DB line (an elasticity of about -0.9) and a positive income effect operating through the local choice of a DB line (an elasticity of 0.704=1.401x0.503, using (13)). On balance, half (=0.971x0.503/0.977) of the income elasticity of DB payments per recipient in equation (14) is attributable to the positive income elasticity of the DB lines.

These results suggest that both the needs effect and resources effects are present, but with offsetting effects. At a given poverty line, richer cities have lower participation rates and spend less on the program (though more per recipient). Although it does not dominate the needs effect, the countervailing resources effect is evident, in that a higher municipal mean income tends to come with a more generous DB line. The resources effect is strong enough to roughly cancel out the needs effect — largely neutralizing the program's ability to reach poor municipalities.

A number of remarks can be made about some possible sources of bias in these findings.

Remark 1: Measurement errors in the survey-based data on municipal incomes are likely to create an attenuation bias in my estimate of the income elasticity of the DB poverty line. The true elasticity is probably higher than estimated above.

Remark 2: There is a second source of bias, due to omitted inter-city differences in the cost-of-living (COL). Consider the reduced form income elasticity of DB spending; let the true income elasticity be δ_1 in:

$$\ln(S_j / COL_j) = \delta_0 + \delta_1 \ln(\bar{Y}_j / COL_j) + v_j \quad (14)$$

²² The same pattern is also evident when one includes smaller urban areas, on top of the 35 main cities studied here; see World Bank (2006).

where COL_j is the latent COL index for city j . We estimate: $\ln S_j = \delta_0 + \delta_1 \ln \bar{Y}_j + \mu_j$ where $\mu_j = (1 - \delta_1) \ln COL_j + \nu_j$. The bias only goes to zero as δ_1 goes to unity, or the income elasticity of the cost-of-living goes to zero.

A clue to the extent of this bias can be found in the provincial cost-of-living indices estimated by Brandt and Holz (BH) (2006). These are not ideal; the most recent estimate is for 2000 and they are for all urban areas of a province rather than the 35 cities studied here. The OLS elasticity of the BH urban COL index across provinces to mean (nominal) income across the 35 cities studied here is 0.213 (t=6.44). Deflating both DB spending and mean incomes by the BH index gives an income elasticity of -0.486; this is higher (in absolute value) than the unadjusted estimate, although it is still not significantly different from zero (t=-1.12). On re-estimating (11) and (12) using the BH deflators one obtains:

$$\begin{aligned} \ln(S_i / COL_i) = & 9.428 - 2.357 \ln(\bar{Y}_i / COL_i) + 0.117(SD_i / COL_i) \\ & \text{(1.22)} \quad \text{(-2.37)} \quad \text{(1.79)} \quad R^2=0.152 \quad (15.1) \\ & + 1.682 \ln(Z_i / COL_i) + \hat{\varepsilon}_i \\ & \text{(2.69)} \end{aligned}$$

$$\ln(S_i / COL_i) = 0.260 - 1.035 \ln(\bar{Y}_i / COL_i) + 1.433 \ln(Z_i / COL_i) + \hat{\varepsilon}_i \quad R^2=0.095 \quad (15.2)$$

(0.05) (-2.06) (2.26)

The results in (11) and (12) are found to be reasonably robust, though the distributional effect is no longer significant at the 5% level.

Ignoring the COL differences probably leads to an overestimation of the true real income gradient of the DB lines, given that the COL is positively correlated with mean income. Using the BH index for the city's province as the deflator for each city I find that the elasticity of real DB line to mean real income is 0.384 (t=4.40). The difference is not large; the income elasticity of the DB line falls from about 0.5 to 0.4.

Allowing for cost-of-living differences across cities will probably also yield a higher (real) income gradient in DB participation. That will be the case if the COL has a (positive) income elasticity less than unity (so that cities are not re-ranked in terms of incomes when one adjusts for the cost-of-living differences).²³ Again we can find a clue to the extent of the bias if

²³ To see why, suppose that the true income elasticity of the DB participation rate is γ_1 in:

$\ln P_j = \gamma_0 + \gamma_1 \ln(\bar{Y}_j / COL_j) + \nu_j$ while the estimated regression is $\ln \bar{P}_j = \gamma_0 + \gamma_1 \ln \bar{Y}_j + \mu_j$

we use the provincial cost-of-living indices estimated by Brandt and Holz. Using the BH I find that the elasticity of DB participation to mean income rises to -1.410 (t=3.65) (instead of -1.197 using the nominal data).

The BH deflators suggest a slightly lower income elasticity of DB payments per recipient of 0.925 (t=4.18) as compared to the unadjusted estimate of 0.977.

Remark 3: The above analysis assumed homogeneity in city size. Against this, there may be fixed administrative costs, yielding scale economies of city size, or congestion effects on the administrative capabilities, yielding diseconomies. While larger cities do tend to have higher mean income, the correlation coefficient is small (the regression coefficient of log population size on log mean income is 0.220, with a t-ratio of 0.51), so only small biases can be expected in estimating the income effects on spending and the DB lines. Controlling for city size, the income elasticity of spending is -0.335, but is still not significantly different from zero (t=-1.08) and the income elasticity of the DB poverty line conditional on city size is 0.493 (t=8.82). In both cases, a significantly positive city-size effect was also evident, controlling for mean income.

Remark 4: The above results are based on the DB payments recorded in the UHSS. Thus they reflect the actual DB program, though measurement errors can also be expected in both recorded DB payments and incomes. (The DB lines are from the independent administrative data and are likely to be measured accurately.) Measurement errors will undoubtedly lower the explanatory power of these regressions. However, it also appears that the program in practice deviates appreciably from its aim of filling the DB poverty gaps. We can calculate from the survey data what would have been required to fill the DB gaps, though only under two key, and questionable, assumptions: (i) that incomes are measured accurately and (ii) that there are no behavioral responses to the program (such as through effects on labor supply).²⁴ Using the survey-based DB gaps to estimate (1), the analogous results to equations (11) and (12) are:²⁵

$$\ln \hat{C}_i = 11.753 - \underset{(2.91)}{2.974} \ln \bar{Y}_i + \underset{(-5.06)}{0.094} SD_i + \underset{(2.61)}{2.374} \ln Z_i + \hat{\varepsilon}_i \quad R^2=0.486 \quad (16.1)$$

where $\mu_j = -\gamma_1 \ln COL_j + \nu_j$. The OLS estimate of γ_1 converges in large samples to $\gamma_1(1-\delta)$

where δ is the elasticity of COL_j to $\bar{Y}_j$. Thus one underestimates γ_1 given that $1 > \delta > 0$.

²⁴ Chen et al. (2006) provide a number of tests for behavioral responses, which do not suggest they are present to any significant degree, although the lack of longitudinal data limits the power of these tests.

²⁵ I also tried squared and cubed terms in log Z but these were (highly) insignificant.

$$\ln \hat{C}_i = 3.561 - 1.761 \ln \bar{Y}_i + 2.089 \ln Z_i + \hat{\varepsilon}_i \quad R^2 = 0.364 \quad (16.2)$$

(1.11) (-4.37) (3.76)

On balance (factoring in the income effect on the DB line) the estimated total income elasticity is negative and is now significant (-0.710, $t = -2.95$). These results suggest that the ways in which local implementation of the program deviated from its impact on overall poverty (as noted in section 4) also promoted geographic inequity, by reducing its effectiveness in reaching poor areas.

5. Horizontal inequity across cities

Recall that horizontal inequality is an implication of a positive income effect on the *Di Bao* poverty lines across cities (Section 2). To assess the extent of this inequity, define a dummy variable, $D_i = 1$ if household i receives DB and $D_i = 0$ if not, and let X_i be a vector of relevant “non-income” factors, including location. The probability of participating in DB is:

$$\Pr(D_i = 1) = N[\phi(\bar{Y}_i) + \beta X_i], \quad (17)$$

where N is the standard normal distribution function (so that equation 17 is estimated as a probit) and $\phi(\cdot)$ is a parametric nonlinear function; on experimenting with different functional forms, I chose a quadratic function of $\ln \bar{Y}_i$, based on the goodness-of-fit.

The X 's in equation (17) should clearly include geographic effects, because location can influence living standards independently of other household characteristics, including income. A complete set of municipality effects is allowed for, by including 34 dummy variables for the 35 cities (Beijing is taken to be the reference).²⁶ The vector X also includes variables related to the dwelling and the observable characteristics of the household, as might be deemed relevant to local assessments of “need.” Discussions with MOCA officials indicated that household assets play an important role independently of income.

The probit estimates of the municipality effects are given in Table 3. Results are given with and without controls for other non-income household characteristics.²⁷

²⁶ Note that the DB line is constant within municipalities, so a regression coefficient for the DB line cannot be identified separately from the geographic effects.

²⁷ The coefficients on the extra control variables are omitted to save space. Complete results for the control variables can be found in Chen et al. (2006).

There is a positive correlation between those effects and the DB lines (Figure 5). The regression coefficient of the municipal effect on the log DB line is 0.903 ($t=2.93$). From Figure 5, the city of Kunming is an outlier; possibly the survey has over-sampled DB participants in Kunming. Dropping Kunming, the regression coefficient rises to 1.001 with a t -ratio of 3.40. However, it is also evident that there are locational factors being captured by the city effects besides differences in the DB lines; the last regression has an $R^2=0.249$. The municipal effects could well be picking up omitted, geographically associated, household characteristics.

While the (unconditional) participation rate falls as city income rises (Section 4), the opposite is true for participation conditional on income and other characteristics. The regression coefficient of the municipal effects on log mean income is 0.502 and is significant at the 2% level ($t=2.52$); if I drop Kunming then the regression coefficient rises to 0.605 ($t=3.30$).²⁸

These effects remain reasonably robust when we add the controls for other “non-income” factors (the second specification in Table 3).²⁹ With the full set of controls, the regression coefficient of the municipal effects on the log DB line is 0.709 with a t -ratio of 1.99, which is not quite significant at the 5% level. However, dropping Kunming, the regression coefficient rises to 0.814 with a t -ratio of 2.39. Again, the city effects are quantitatively large.

So one finds that, at given observed household characteristics, the higher the mean income of the city of residence the better one’s chance of accessing the program. The differences in the size of the municipal effects on participation in Table 3 are quantitatively significant. This can be seen if we ask what income difference would compensate for the difference in the city coefficients holding the probability of participation constant. The existence of the quadratic term complicates the calculation, but simply graphing the predicted scores from Table 3 is sufficient to demonstrate the point. Figure 6 gives the predicted scores for selected cities. Consider, for example, one of the richest cities, Shanghai, and one of the poorest, Nanchang (Table 2). It can be seen that, over the interval in which the scores overlap, the compensating difference in log income is about unity. In other words, a household in Shanghai

²⁸ As we have noted, data are not available on the inter-city differences in the cost of living. However, by similar reasoning to section 2, it can be argued that this data problem will lead us to underestimate the real income gradient in the conditional city effects on DB participation.

²⁹ The control variables included household demographics, age of head, education attainments, size, age, quality and ownership status of dwelling, selected consumer durables, health status of head, financial assets, occupation and sector dummy variables; details can be found in Chen et al. (2006).

with more than double the income of an observationally identical household in Nanchang would achieve the same probability of participation.

This effect largely operates through the fact that richer cities set higher DB lines. There are no statistically convincing signs that the income effect operates independently of the DB line; on including the DB line as a control variable, the regression coefficient of the city effect on log mean income drops to about half its value and is not significantly different from zero.

So there are convincing signs of horizontal inequity in the program, stemming from its decentralized design and financing. Holding other observed characteristics constant, people in better off cities (in terms of mean income) are more likely to receive help from the program.

6. Conclusions

Decentralized implementation of an anti-poverty program relieves the center of the need to identify eligible recipients, which local authorities may well be in a better position to do. However, decentralization has its costs too — costs that may well be hidden from the center. The literature has pointed to concerns about migration responses and capture by local elites. This paper has focused on another concern, stemming from the fact that the choices made by local authorities in deciding who is eligible need not be consistent with the center's objectives and will typically be constrained by local resources. Even without local-capture problems, the geographic inequities under decentralization can so diminish a program's impact that the information advantage of decentralization becomes a moot point. Furthermore, the information needed for setting corrective cost-sharing or inter-jurisdictional transfers is implausible — no less demanding than that required for a fully centralized scheme.

China's *Di Bao* program provides an interesting case study. This is an ambitious attempt to eliminate extreme income poverty in urban China, using geographically decentralized implementation of cash transfers aiming to guarantee a minimum income for urban residents. Each municipality is free to decide who is eligible, by setting its own minimum income. On combining evidence from an unusually large household survey (representative for each of the 35 largest cities) with administrative data on the poverty lines chosen by local authorities, the paper finds that better-off cities are able to support higher poverty lines for program eligibility and hence higher participation rates at given levels of need. In practice, the locally chosen income minima are more like relative poverty lines. Thus equally poor families in different cities have

very different levels of access to the program, with the poor in poor cities typically faring the worst. This happens even though the center provides some degree of differential cost-sharing, apparently favoring poorer municipalities.

The overall cross-city income gradient in program spending is negative, although quantitatively small and statistically insignificant. Nonetheless, while the needs effect remains dominant, it is clear that the local resource constraint has greatly attenuated the program's ability to reach poor areas. The results also suggest that the program works in practice rather differently from its intended design, and these local departures from the center's design further attenuated the program's ability to reach poor areas.

The main policy implication from this analysis is that greater attention needs to be given to the costs of decentralizing anti-poverty programs. Given those costs, there is no reason to presume that centrally-imposed eligibility criteria — albeit based on imperfect information — are dominated by decentralized implementation. In the case of a means-tested program such as *Di Bao*, the program may well have greater impact on poverty if the poverty line is set centrally, taking account of whatever information the center has on cost-of-living differences. Naturally, there will still be aspects of the program that can only be managed efficiently at the local level, including identification and verification of who is eligible. However, China might be better advised to follow the more standard recommendations from the public finance literature to centralize the key design parameters of its future redistributive policies, although for rather different reasons than the traditional efficiency arguments based on migration responses.

References

- Alderman, Harold, 2002, "Do Local Officials Know Something We Don't? Decentralization of Targeted Transfers in Albania," *Journal of Public Economics*, 83(3): 375-404
- Bardhan, Pranab, 2002, "Decentralization of Governance and Development," *Journal of Economic Perspectives* 16(4): 185-205.
- Bardhan, Pranab and Dilip Mookherjee, 2000, "Capture and Governance at Local and National Levels," *American Economic Review, Papers and Proceedings* 90(2): 135-139.
- Boadway, Robin, 2003, "National Taxation, Fiscal Federalism and Global Taxation," Discussion Paper No. 2003/87, World Institute for Development Economics Research, United Nations University.
- Brandt, Loren and Carsten Holz, 2006, "Spatial Price Differences in China: Estimates and Implications," *Economic Development and Cultural Change* 55: 43-86.
- Buchanan, James, 1950, "Federalism and Fiscal Equity," *American Economic Review* 40: 583-99.
- Chen, Shaohua, Martin Ravallion and Youjuan Wang, 2006, "*Di Bao*: A Guaranteed Minimum Income in China's Cities," Policy Research Working Paper, WPS 3805, Washington DC, World Bank.
- Coady, David, Margaret Grosh and John Hoddinott, 2004, "Targeting Outcomes Redux," *World Bank Research Observer* 19(1): 61-86.
- Cornia, Giovanni and Frances Stewart, 1995, "Two Errors of Targeting," in Dominique van de Walle and Kimberly Nead (eds) *Public Spending and the Poor*, Johns Hopkins University Press for the World Bank.
- Feldstein, Martin and Marian Vaillant Wrobel, 1998, "Can State Taxes Redistribute Income?" *Journal of Public Economics* 68(3): 369-396.
- Galasso, Emanuela and Martin Ravallion, 2005, "Decentralized Targeting of an Anti-Poverty Program," *Journal of Public Economics* 85: 705-727.
- Kanbur, Ravi and Xiaobo Zhang, 2005, "Fifty Years of Regional Inequality in China: a Journey Through Central Planning, Reform, and Openness," *Review of Development Economics* 9 (1): 87-106.
- Khemani, Stuti, 2006, "The Political Economy of Equalization Transfers." In *Fiscal Equalization: Challenges in the Design of Intergovernmental Transfers*, Edited by Jorge

- Martinez-Vazquez and Robert Searle, Springer Verlag.
- Mansuri, Ghazala and Vijayendra Rao, 2004, "Community-Based and -Driven Development," *World Bank Research Observer* 19(1): 1-40.
- McLure, Charles Jr., 1995, "Comment on Prud'homme," *World Bank Research Observer* 10(2): 221-226.
- Oates, Wallace, 1972, *Fiscal Federalism*, New York: Harcourt Brace Jovanovich.
- _____, 1999, "An Essay on Fiscal Federalism," *Journal of Economic Literature* 37: 1120-49.
- O'Keefe, Philip, 2004, "Social Assistance in China: An Evolving System," mimeo, World Bank, Washington DC.
- Park, Albert, Scott Rozelle, Christine Wong, Changqing Ren, 1996, "Distributional Consequences of Reforming Local Public Finance in China," *China Quarterly*, 147 (Sept.): 751-778.
- Prud'homme, Rémy, 1995, "The Dangers of Decentralization," *World Bank Research Observer* 10(2): 201-220.
- Ravallion, Martin, 2007, "Miss-targeted or Miss-measured?" *Economics Letters*, forthcoming.
- Ravallion, Martin and Shaohua Chen, 2007, "China's (Uneven) Progress Against Poverty," *Journal of Development Economics*, 82(1): 1-42.
- Shah, Anwar and Chunli Shen, 2006, "The Reform of Intergovernmental Transfer System to Achieve a Harmonious Society and a Level Playing Field for Regional Development in China," Policy research Working Paper WPS4100, World Bank, Washington DC.
- Shen, Chunli, Jing Jin and Heng-fu Zou, 2006, "Fiscal Decentralization in China: History, Impact, Challenges and Next Steps," mimeo, Development Research Group, World Bank.
- Tsui, Kai-yuen, 2005, "Local Tax System, Intergovernmental Transfers and China's Local Fiscal Disparities," *Journal of Comparative Economics* 33: 173-196.
- West, L., and C.P. Wong, 1995, "Fiscal Decentralization and Growing Regional Disparities in Rural China: Some Evidence on the Provision of Social Services," *Oxford Review of Economic Policy*, 11(4): 70-84.
- World Bank, 2006, "The Urban *Di Bao* Program," China Poverty Assessment Brief, World Bank, Washington DC.
- _____, 2007, *Urban Di Bao in China: Building on Success*, World Bank, Human

Development Unity, South Asia, World Bank.

Zhang, Xiaobo, 2006, “Fiscal decentralization and Political Centralization in China: Implications for Growth and Inequality,” Research Paper 2006/93, UNU-WIDER, Helsinki.

Table 1: Numerical example (Case 3)

	“Rich” region	“Poor” region
Population share	60%	40%
Mean income ($\bar{Y}$)	\$300	\$200
Center’s poverty line (Z^*)	\$200	\$200
Headcount index (H)	0.10	0.90
Mean income of the poor ($\bar{Y}^Z$)	\$100	\$50
Spending under centralized program to fill poverty gaps ($C(Z^*)$)	\$10	\$135
Locally welfare-maximizing spending under decentralization ($C(Z_j)$) (see note)	\$200	0
Center’s share of cost	\$100	0

Notes: (i) Local agent’s welfare function is $400 \ln[\bar{Y}_j - 0.5.C_j(Z_j)] + C_j(Z_j)$, implying welfare-maximizing spending levels of $C(Z_j) = 2\bar{Y}_j - 400$; (ii) the center’s aggregate spending is \$60 per capita in both cases.

Table 2: Summary statistics by city

	(1)	(2)	(3)	(4)
	Mean income (Yuan per person per year)	DB line (Yuan per person per year)	DB participation rate (% pop.)	DB payments per DB recipient (Yuan per person per year)
Beijing	13357	3480	2.53	535.20
Tianjin	9789	2892	6.26	239.88
Shijiazhuang	8001	2460	3.29	162.76
Taiyuan	7855	2052	2.49	187.16
Huhehaote	7441	2160	1.08	260.72
Shenyang	6345	2460	4.74	249.51
Dalian	78355	3312	3.67	288.75
Chuangchun	7380	2028	4.40	146.80
Harbin	6812	2400	5.15	239.03
Shanghai	13767	3480	6.41	353.98
Nanjing	11557	2880	2.66	320.67
Hangzhou	14882	3420	0.65	549.09
Ningbo	15846	3120	2.42	596.35
Hefei	8211	2520	5.66	179.62
Fuzhou	10452	2520	0.93	213.97
Xiamen	14615	3480	2.13	245.90
Nanchang	7227	1980	4.44	153.10
Jinan	8597	2496	4.39	284.37
Qingdao	9235	2760	1.59	372.01
Zhengzhou	7732	2400	1.33	260.37
Wuhan	8410	2640	5.59	244.03
Changsha	10770	2400	6.02	212.28
Guangzhou	14039	3600	1.31	623.32
Shenzhen	26036	3600	1.08	497.90
Nanning	7573	2280	3.66	85.26
Haikou	8039	2652	1.58	139.33
Chongqing	6007	2220	12.13	236.99
Chengdu	9701	2136	1.84	182.13
Guiyang	7521	1872	6.20	206.62
Kunming	7231	2280	26.81	155.91
Xian	7901	2160	4.08	240.90
Lanzhou	6895	2064	5.08	232.62
Xining	7505	1860	3.92	165.51
Yinchuan	7515	2040	6.09	179.06
Wulumuqi	8351	1872	1.87	215.72
Sample mean	9951	2715	3.91	270.19

Sources: (1), (3) and (4) are calculated from the UHSS, while (2) is from administrative records of MOCA; see section 3 for details.

Table 3: Probits for *Di Bao* participation

	Coefficient	t-ratio	Coefficient	t-ratio
Log income per capita	0.9661	4.02	0.2725	1.09
Squared log income per capita	-0.1404	-8.88	-0.0668	-4.08
Controls for household characteristics	No		Yes	
City coefficients (Reference=Beijing)				
Tianjin	0.0994	1.75	-0.0681	-0.97
Shijiazhuang	-0.5859	-7.82	-0.2388	-2.78
Taiyuan	-0.8160	-8.77	-0.5976	-5.42
Huhehaote	-1.4190	-12.16	-1.3597	-11.08
Shenyang	-0.5663	-9.71	-0.5294	-7.89
Dalian	-0.4863	-7.33	-0.5717	-7.65
Chuangchun	-0.5863	-7.22	-0.3419	-3.74
Harbin	-0.6085	-10.16	-0.5388	-7.81
Shanghai	0.6629	11.78	0.7573	8.8
Nanjing	-0.3226	-5.07	-0.1851	-2.18
Hangzhou	-0.6560	-5.10	-0.3990	-2.72
Ningbo	-0.1917	-1.71	0.0490	0.36
Hefei	-0.2452	-2.77	0.1415	1.34
Fuzhou	-0.7722	-6.15	-0.5173	-3.8
Xiamen	-0.1928	-1.58	-0.3417	-2.32
Nanchang	-0.6285	-7.43	-0.2752	-2.77
Jinan	-0.5034	-7.39	-0.4849	-6.06
Qingdao	-0.8319	-8.02	-0.7061	-5.58
Zhengzhou	-1.0734	-10.47	-0.7907	-6.65
Wuhan	-0.2594	-4.48	-0.0319	-0.42
Changsha	-0.0598	-1.05	0.0645	0.84
Guangzhou	-0.4675	-4.13	-0.6260	-5.01
Shenzhen	-0.0389	-0.13	0.3040	0.97
Nanning	-0.9349	-8.41	-0.5367	-4.17
Haikou	-1.3432	-10.31	-1.1193	-7.41
Chongqing	-0.2114	-3.70	0.0532	0.7
Chengdu	-0.8323	-6.19	-0.6369	-3.95
Guiyang	-0.6388	-7.80	-0.6384	-6.52
Kunming	0.8216	10.20	1.0858	10.24
Xian	-0.3825	-3.49	-0.3491	-2.64
Lanzhou	-0.5356	-7.05	-0.4723	-5.36
Xining	-0.6486	-7.86	-0.5285	-4.84
Yinchuan	-0.3584	-4.24	-0.1434	-1.55
Wulumuqi	-1.1191	-10.51	-1.0720	-8.75
Constant	0.4066	0.45	0.3995	0.22
# of obs.	76762		76443	
Pseudo R ²	0.3704		0.4718	

Figure 1: *Di Bao* spending plotted against mean income; 35 main urban areas of China

Figure 2: The municipal income effect on DB payments per recipient

Figure 3: The municipal income effect on DB participation

Figure 4: *Di Bao* lines against mean incomes

Figure 5: City-effects on participation in the *Di Bao* program against the *Di Bao* line

Figure 6: Selected city effects on DB participation as a function of income