Decentralizing Eligibility for a Federal Antipoverty Program: A Case Study for China

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In theory, the informational advantage of decentralizing the eligibility criteria for a federal antipoverty program could come at a large cost to the program's performance in reaching the poor nationally. Whether this happens in practice depends on the size of the local-income effect on the eligibility cutoffs. China's Di Bao program provides a case study. Poorer municipalities adopt systematically lower thresholds—roughly negating intercity differences in need for the program and generating considerable horizontal inequity, so that poor families in rich cities fare better. The income effect is not strong enough to undermine the program's overall poverty impact; other factors, including incomplete coverage of those eligible, appear to matter more. JEL codes: H70, I32, I38, O18

The public finance literature generally recommends that redistributive transfers aiming to reduce poverty should be the responsibility of the central government in a federal system.[1] The main argument against decentralizing such programs is that doing so will induce migration responses, which will be costly and undermine the redistributive effort.

Many countries are not following this policy recommendation. It is quite common for central governments, particularly in developing countries, to decentralize key aspects of the implementation and funding of their antipoverty programs. Typically, the center continues to provide broad guidelines and at least partial cofunding, but is relieved of decisions on the specific beneficiaries of that funding. Informational asymmetries have been the main justification for such decentralized redistributive policies. Advocates argue that, for assessing eligibility, local agents are better informed than the center about local conditions. These informational problems are believed to have special salience in

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1. The classic exposition is Oates (1972), also see the more qualified view in Oates (1999).

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developing countries. However, the literature also points out that the same information problems create prospects for capture by local elites, subverting the center's aims.[2]

Another important stylized fact is large geographic disparities in average incomes in developing countries. As this article will argue, these disparities can be associated with perverse geographic inequities in the outcomes of a decentralized antipoverty program. Indeed, the induced interjurisdictional disparities in program spending can far exceed even large disparities in mean incomes. Then, under certain conditions decentralization can severely limit the scope for reducing poverty as judged by consistent national criteria. The gains to the center in devolving power over beneficiary selection may come at a high price in the program's 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 poverty as an adaptation to its budget constraint. Geographic inequity arises as poor areas spend less on their poor people. Horizontal inequity also emerges as equally poor people are treated differently depending on where they live. Developing countries might then be better advised to follow the more standard recommendations from the public finance literature to centralize the key design parameters of their redistributive policies—although for rather different reasons from the traditional efficiency arguments based on migration responses.

Such concerns are not new. In the past they have been seen to yield a compelling equity case for central action, aiming to ensure 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 inequities by differential cost-sharing or intergovernmental transfers.[3] However, the extent to which such corrective policies are feasible in practice remains a moot point, given the same information asymmetries that have motivated the decentralization of antipoverty programs. Indeed, as this article 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 hardly suggests strong geographic redistribution of spending and fiscal burdens.[4] Political influence on the outcomes can also be expected, and it would not be too surprising if

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

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

4. In China, the redistributive impact of the system of intergovernmental transfers is known to be quite weak; see Tsui (2005), Shen, Jin, and Zou (2006), and Shah and Shen (2006).

this favored better-off areas.[5] The case for believing that cost-sharing or transfers can solve the problem is far from obvious.

The article studies these issues in the context of an antipoverty program in which means-tested transfers aim to bring everyone up to an ensured minimum income. In an effort to redress China's sharply rising income inequality and signs of weak social protection for vulnerable groups, the central government introduced the Di Bao program in 1999. The program aims to provide all urban households that are registered in a specified locality with a transfer payment sufficient to bring their incomes up to a predetermined poverty line. Obtaining registration in a new location is generally a difficult process in China (not least for the poor), so in practice program eligibility is confined to well-established local residents. The program started in Shanghai in 1993, and as it was deemed successful became a national (federal) program with formal regulations issued by the State Council in 1999. The program expanded rapidly and by 2003 participation had leveled off at 22 million people a year. The program is administered by the Ministry of Civil Affairs (MOCA).

Like many social spending programs in China, implementation of Di Bao is decentralized.[6] While the national and provincial governments provide guidelines and cofinancing, the selection of beneficiaries is under municipal control. Individual municipalities determine their Di Bao eligibility line and finance the transfers in part from local resources. The center provides some guidance on how these lines are to be set, not only mentioning the need to ensure that basic consumption needs are met, given prevailing prices, but also noting local fiscal constraints (O'Keefe 2004; World Bank 2007). Claimants must apply to the local (county-level) civil affairs office for Di Bao assistance, typically through their local residential committee, which administers the program's day-to-day activities. There is also a community vetting process, whereby the names of proposed participants are displayed on notice boards and community members are encouraged to identify any undeserving applicants.[7]

In 2003–04 about 60 percent of the program's cost was financed by the center. The share varied across provinces, although data are not available on the precise shares. A State Council circular in 2000 says that "central finance will render support to areas with financial difficulties at its discretion," and a 2001 State Council circular clarifies that central funding was available for

5. Khemani (2006) reviews the literature on political influences on intergovernmental transfers for regional equalization.

6. Generic concerns have been voiced in the literature about the implications of China's high fiscal decentralization for the country's poor areas; see, among others, West and Wong (1995), Park and others (1996), Kanbur and Zhang (2005), Shen, Jin, and Zou (2006), and Zhang (2006).

7. This raises concerns about stigma effects. World Bank (2007) reports results of a survey of Di Bao participants in Liaoning Province that 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.

provinces with financial difficulties and high demand for Di Bao.[8] 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 suggests an effort to set higher central cost shares in poorer provinces. However, in the context of public spending, generally, intergovernmental transfers are also known to be subject to political negotiation that does not typically favor poorer provinces (Shen, Jin, and Zou 2006). It would be surprising if Di Bao were immune to these political effects, although little is known about their specific form.

That local authorities retained power over the Di Bao thresholds undoubtedly reflects in part the center's lack of information on differences in the cost of basic needs in different cities. Government officials (in interviews with the author) said that the advantage of involving local community groups is their greater knowledge of local conditions, including the cost of living. However, the center also likely believed that there were limits to how much it could credibly control the local authorities, even with good information. The history of the program—notably Di Bao's emergence from a local initiative—appears to have also influenced the extent of decentralization in implementing the scaled-up national version. Central officials said that local municipalities had the right to set their own thresholds, given that Di Bao had started as a local program and the municipalities cofinance the program.[9]

However, in interviews, central MOCA officials also recognized the likelihood that poorer municipalities might choose lower real Di Bao thresholds because of lack of resources. The central officials considered this to be an undesirable feature of the program. They appear to view the program's objective as reducing absolute poverty nationally, rather than relative poverty as judged by each locality. The authorities hoped that more favorable cost-sharing arrangements in poor cities would help avoid this problem. This article will try to see whether that is the case.

The article begins by outlining a stylized program model, which demonstrates just how much decentralized beneficiary selection can reduce the program's overall poverty impact as judged by consistent national criteria. In one example, a central budget sufficient to eliminate poverty leaves 90 percent 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 ensure equal treatment of ex ante equals is to eliminate the inequality in provision between rich and poor areas.

8. This information is from correspondence with Philip O'Keefe, then lead social protection specialist for East Asia at the World Bank.

9. This type of central reliance on local governments is a long-standing feature of China's social policies.

The article then studies the Di Bao program using a household survey that is representative at the level of each of China's 35 largest cities, allowing city-level analysis. These data are used to explore intercity differences in spending and other program parameters and to examine the implications for the program's impacts on poverty. The results indicate that poorer municipalities tend to set less generous eligibility criteria, which diminishes, but does not eliminate, the program's efficacy in poor municipalities. Overall, the extent to which decentralized eligibility attenuated the program's impact turns out to be very small. While there are some concerns about measurement error, it appears likely that the program's operation in practice has reduced the cost of the decentralized eligibility criteria to the program's performance in reaching poor areas and poor people nationally. However, there is evidence of horizontal inequity in the form of large intercity differences in the probability of participation at given (observable) household characteristics.

I. Theoretical Model of the Antipoverty Program

The following model is a stylized version of the scheme that will be studied empirically later in the article. It is assumed that the central government's objective for the program is to provide cash transfers sufficient to bring everyone in municipality j $(=1,..,n)$ up to an income level Z_j^* sufficient not to be deemed "poor." The model deliberately ignores political economy considerations facing the center: it is obvious that if the center does not in fact aim to reduce poverty through this program—trading this objective off against a desire to placate middle-income groups, for example—then the outcomes will fall short of the maximum impact on poverty for a given budget. Instead, the aim here is to explore whether decentralization of the eligibility criteria could on its own attenuate the poverty impact, even when reducing poverty is the center's objective.

In keeping with the fact that this is a federal program, poverty is defined in absolute terms, so that two people with the same real income are treated the same way wherever they live. Thus Z_j^* is the cost of a reference level of welfare (utility), which is fixed nationally. By an appropriate choice of a cost of living index for normalizing both incomes and poverty lines, $Z_j^* = Z^*$ for all j.

The resulting public expenditure will be distributed across municipalities such that the higher their poverty gap, the higher their spending allocation. Spending per capita in municipality j with income distribution $F_j\ (y)$ is

$$\mathbf{C}_j^* = \int_0^{Z^*} (Z^* - y)\mathrm{d}F_j(y) = (Z^* - \overline{Y}_j^{Z^*})H_j^* \tag{1}$$

where $H_j^* \equiv F_j\ (Z^*)(>0)$ is the proportion of the population below the poverty line (the headcount index or poverty rate), and $\overline{Y}_j^{Z^*}$ is the mean income of the poor when the poverty line is Z^*. The cost of the program is implicitly a function of all parameters of the distribution function, $F_j(y)$. These include the mean, $\overline{Y}_j$, and the distribution of incomes relative to the mean, which is taken to be fully described by a vector of parameters, L_j, representing the Lorenz curve in municipality j. C_j^* is also a function of Z^* at a given $F_j(y)$. It is convenient to rewrite equation (1) as

$$\mathbf{C}_j^* = C(\overline{Y}_j, L_j, Z^*). \tag{2}$$

The problem is that the center does not have the information needed to implement this ideal program. It has access to a national sample survey that includes household incomes or expenditures, but it can observe the nominal distribution of income only in provinces or municipalities for which the sample size is large enough to be considered representative. It is implausible that most national surveys would be representative at the levels of government at which the central government would 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 rare to have spatial cost of living indexes. Additionally, there are likely to be idiosyncratic differences in needs (even without price differences) because of differences in climate and the mix of other public programs, among other reasons.

With decentralized implementation the center gives each municipality the power to select beneficiaries, but requires cofinancing to help control the program. Local agents are instructed to fill poverty gaps but are free to determine the local poverty line. Total spending on the program in municipality j is given by $C(\overline{Y}_j, L_j, Z_j)$, where Z_j is the municipality's chosen Di Bao poverty line. The possibility of relocation in response to the variation in Z_j is closed off. This can be rationalized by either prohibitive costs of moving or residency requirements (only long-standing residents are entitled to the program).

How will local spending vary with mean income? Intuitively, two effects might be expected to be working in opposite directions. A poorer municipality will have fewer resources for fighting poverty—call this the "resources effect." But a municipality with low mean income will tend to have a high poverty rate—call this the "needs effect." The qualifier "tend to" is important, since there can also be a "distributional effect," potentially offsetting the tendency for municipalities with a lower mean income to have a higher poverty rate. To see the various factors that come into play more clearly, differentiate equation

(2) with respect to the mean as follows:

$$\text{(3)} \qquad \frac{\mathrm{d}C(\overline{Y}_j, L_j, Z_j)}{\mathrm{d}\overline{Y}_j} = \left[\frac{\mathrm{d}C(\overline{Y}_j, L_j, Z_j)}{\mathrm{d}\overline{Y}_j}\right]_{Z=\text{const}} + H_j \frac{\partial Z_j}{\partial \overline{Y}_j}$$

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

$$\text{(4)} \qquad \left[\frac{\mathrm{d}C(\overline{Y}_j, Z_j, L_j)}{\mathrm{d}\overline{Y}_j}\right]_{Z=\text{const}} = \left(\frac{\partial C}{\partial \overline{Y}_j}\right)_{L=\text{const}} + \frac{\partial C}{\partial L_j}\frac{\mathrm{d}L_j}{\mathrm{d}\overline{Y}_j}$$

where

$$\text{(5)} \qquad \left(\frac{\partial C}{\partial \overline{Y}_j}\right)_{L=\text{const}} = -\int_0^{H_j} \frac{\partial y_j(p)}{\partial \overline{Y}_j}\mathrm{d}p = -\frac{H_j \overline{Y}_j^Z}{\overline{Y}_j} = -\omega_j$$

where $y_j(p)$ is the quantile function (inverse of the distribution function, $p = F_j(y_j)$) and ω_j $(0 < \omega_j < 1)$ is the income share of the poor.[10] The first term on the right side of equation (4) 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 $\mathrm{d}L_j/\mathrm{d}\overline{Y}_j$—could have either sign. The expansion path for spending can be said to be distribution neutral if this aggregate distributional effect is zero.

The direction and size of the resources effect depend 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, α_j, where $0 < \alpha_j \leq 1$ for all j. The center chooses α_j to ensure 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 $\overline{Y}_j - \alpha_j C_j$, where $\overline{Y}_j$ is gross income. The program's local income share is $s_j \equiv \alpha_j C_j/\overline{Y}_j$.

In characterizing the behavior of local government agents, it can be presumed that they do not care solely about reducing poverty. Each municipality is assumed to have preferences over spending on the program and other uses of local income, both valued positively. These preferences can be taken to embody the local political economy, in that different local municipalities are taken to have different preferences, which reflect the local political and economic factors that influence the tradeoffs drawn between spending on the anti-poverty program and other uses of public money.

10. The derivation of equation (5) exploits the fact that, on holding the Lorenz curve constant (intuitively, holding inequality constant), it must be the case that all income levels change at the same proportionate rate, implying that the quantile function has an elasticity of unity with respect to the mean: $\partial \ln y(p)/\partial \ln \overline{Y} = 1$. Also note that $C_j = \int_0^{H_j} (Z - y_j(p))\, \mathrm{d}p$.

In rationalizing the assumption that local authorities value spending on poverty reduction, they can be thought either to care intrinsically about their impact on poverty or to view it as instrumentally important. The second case rests on the fact that the program attracts cofinancing resources from the center. Reaching a larger share of the local population through the antipoverty program may buttress the position of local authorities, making it more likely that they stay in power.[11] The program's local impact on poverty is measured by the poverty gap, consistent with the program's stated objective.

More formally, let each municipality have a preference ordering over local spending on the program and income net of local program spending as represented by the function:

$$W_j = W_j(\overline{Y}_j - \alpha_j C_j, C_j). \tag{6}$$

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[12]

$$\alpha_j W_{jY}(\overline{Y}_j - \alpha_j C_j, C_j) = W_{jC}(\overline{Y}_j - \alpha_j C_j, C_j) \tag{7a}$$

$$\alpha_j^2 W_{jYY} - 2\alpha_j W_{jYC} + W_{jCC} < 0. \tag{7b}$$

(Subscripts on W denote partial derivatives.) Implicitly differentiating (7a) with respect to $\overline{Y}_j$:

$$\frac{dC_j}{d\overline{Y}_j} = \frac{\alpha_j W_{jYY} - W_{jYC}}{\alpha_j^2 W_{jYY} - 2\alpha_j W_{jYC} + W_{jCC}}. \tag{8}$$

The direction of the municipal income effect in equation (8) is ambiguous under the assumptions made so far. However, four special cases will help interpret the result in equation (8).

Case 1: Suppose that higher municipal income lowers the marginal welfare of program spending ($W_{YC} < 0$) and that the municipality's objective is linear in income ($W_{YY} = 0$) then it is immediately clear from equation (8) that $dC_j/d\overline{Y}_j < 0$; 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 $dC_j/d\overline{Y}_j > 0$; poorer

11. A city government in China that was widely seen to neglect its local population would be unlikely to stay in power very long.

12. 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 cofinancing requirement the municipality will choose a corner solution in which all its residents are deemed to be "poor."

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 cofinancing share:

$$\frac{dC_j}{d\overline{Y}_j} = \frac{1}{\alpha_j} \geq 1. \tag{9}$$

Not only will the resources effect dominate, but the total income effect will be no less than unity. At a 50 percent cost share (say), program spending will rise \$2 for each \$1 gain in mean municipal income. Furthermore, local spending on the program could be highly 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. Consider two regions, one poor and one rich. Given the parameter values in table 1, filling the poverty gaps relative to a single national (real) poverty line would require \$135 in the poor region and \$10 per capita in the rich region. It can be seen that 90 percent of the national poverty gap (the population-weighted aggregate of $(Z^* - \overline{Y}_j^Z)H_j$ across the two regions) is in the poor region. Under the Case 3 welfare function, $400\ln(\overline{Y}_j - 0.5C_j) + C_j$ (with a 50 percent cost share), and decentralization, the entire program budget ends up going to the rich region, with none to the poor region. Instead of eliminating absolute poverty, as judged by the national poverty line, the decentralized program will leave 90 percent of the problem untouched.

Case 4: A further insight into just how powerful the resources constraint can be is obtained by combining Case 3 with the assumption of distribution neutrality ($dL_j/d\overline{Y}_j = 0$). Then one obtains the following simple formulas for the

TABLE 1. Numerical Example (Case 3)

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

[a]Local agent's welfare function is $400\ln[\overline{Y}_j - 0.5.C_j(Z_j)] + C_j(Z_j)$, implying welfare-maximizing spending levels of $C(Z_j) = 2\overline{Y}_j - 400$. The center's aggregate spending is \$60 per capita in both cases.

Source: Author's calculations.

decomposition in equation (3):

$$\left[\frac{\partial C_j}{\partial \overline{Y}_j}\right]_{Z=\text{const}} = -\omega_j < 0 \text{ (needs effect)} \tag{10a}$$

$$H_j \frac{\partial Z_j}{\partial \overline{Y}_j} = \frac{1}{\alpha_j} + \omega_j > 0 \text{ (resources effect).} \tag{10b}$$

This suggests that differences in needs may play a modest role under Case 4. In a municipality with typical income inequality and a medium-size program, ω_j will be quite small—unlikely to exceed 0.05. With a 50 percent cost share, the resources effect will be 2.05, 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, meaning that people who are identical ex ante are not treated equally under the program ex post.[13] This happens in two ways. First, 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 nonoverlapping support (in the income dimension) induced by the income gradient of the poverty line. Second, 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.

In principle, such geographic inequities (both vertical and horizontal) can be redressed by a differential cost-sharing arrangement. To see what would be required, note that Z_j satisfying equation (7a) can be written as: $Z_j = Z_j\ (\overline{Y}_j, \alpha_j)$. Consider the conditional cost share, $\alpha_j^* = \alpha_j^*(\overline{Y}_j,\ Z^*)$, defined implicitly by $Z^* = Z_j\ (\overline{Y}_j,\ \alpha_j^*)$. If the center sets α_j^*, it will ensure that under decentralization each municipality chooses the national poverty line, Z^*. (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 α_j^*, $j = 1,..,n$, there will be no municipal income effect on the poverty lines.

However, the data requirements for such a cost-sharing formula are considerable. The function $Z_j\ (\cdot)$ 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 the local level. This suggests that the cost-sharing arrangements found in practice may be subject to severe information and

13. By contrast, "vertical inequality" here refers to differences in transfer receipts between individuals at different levels of income (irrespective of where they live).

computational constraints on the extent to which the biases against poor areas can in fact be eliminated.

The rest of this article explores these issues in the context of China's Di Bao program. Section II describes the data. Section III examines the municipal income effect on program spending and implements the decomposition into a needs effect and resources effect as defined above. The key finding is that a strong local resources effect (operating through the setting of local eligibility criteria) is essentially neutralizing the program's ability to reach poor municipalities.

These findings raise two further empirical issues, which are taken up in Sections IV and V. The first concerns the implications for the program's overall goal of reducing urban poverty; Section IV shows that the resources effect attenuated the scheme's overall impact on poverty but that this effect was quantitatively small; incomplete coverage and too low a benefit level were more important reasons for the program's low overall impact on poverty. The second issue concerns the implications for horizontal equity. Consistent with the arguments above, Section V shows that the decentralization of eligibility criteria generated considerable horizontal inequity; the poor living in relatively rich cities received more help from the program than otherwise identical families in poor cities.

II. Data

The empirical analysis is based on two data sources. The first is the available set of (published and unpublished) administrative records for the program. Most important, 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. However, independent data were not available on Di Bao spending at the municipal level.

The second data source is China's Urban Household Short Survey (UHSS) for 2003–04. The UHSS was conducted by the Urban Household Survey (UHS) Division of the National Bureau of Statistics (NBS) as a first step in constructing the sample for the regular UHS, which has a much longer questionnaire, but much smaller sample size. This article uses the UHSS sample for the 35 largest cities—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 of each of the 35 largest cities; the sample sizes vary from 450 (in Shenzhen) to 12,000 (in Beijing). Thus intercity comparisons are reasonably reliable, though (of course) sampling and nonsampling errors are still to 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 Di Bao lines.[14] The entire data set has been cleaned by NBS

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

staff and made available for this research. While the UHSS is a relatively short survey, it permits measurement of a fairly wide range of household characteristics, including income. Chen, Ravallion, and Wang (2006) describe the survey data in greater detail. Table 2 provides summary statistics by city. The UHSS did not exist when Di Bao was being designed. In particular, Di Bao poverty lines had been set prior to the survey.

Five data problems are notable. First, the urban surveys conducted by the NBS are thought to under-represent the urban poor, notably the "floating population"—rural migrants to urban areas who still have rural registration. This problem arises from the fact that the sample frame of the NBS surveys was based on registration rather than on street addresses. This problem has become less serious because street address sampling was introduced into the urban surveys after 2002, but some observers think that a bias remains. The problem is of less concern in the present context, given that rural migrants are not eligible for the program.

Second, the survey measured household income from responses to the single question "What is your household's total income?" (although 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 the NBS's UHS, although this survey is too small for city-level analysis. To some extent, the measurement errors will average out at the city level, but errors are still to be expected. Some implications of this problem will be pointed out along the way, as well as some robustness tests.

Third, there is no municipal cost of living index for China. The Di Bao lines may reflect (at least in part) cost of living differences. The likely biases due to this problem will be discussed, and it will be argued that the main results are robust.

Fourth, given that municipal program data were not available, estimates for program spending were based on survey responses on income received from the program. This excludes administrative costs. But probably more worrying is that self-reported Di Bao receipts are likely to be measured with error. If these are classical (white-noise) errors, they will lower the explanatory power of the regressions reported below without creating biases. However, the possibility of nonclassical errors cannot be ruled out (see below for the implications of this).

Fifth, that this is a single cross-sectional survey limits the possibilities for allowing for behavioral responses at the household level to Di Bao payments (such as through effects on labor supply). Chen, Ravallion, and Wang (2006) provide several tests for behavioral responses, which do not suggest that they are present to any significant degree, although the lack of longitudinal data limits the power of these tests. In measuring poverty impacts of the program, the income gain is assumed to be the Di Bao transfer payment.

Related to these data concerns, there is an issue of whether, in studying city-level income effects on Di Bao spending (gross), mean income of a city or mean

TABLE 2. Summary Statistics by City

	Mean income (yuan per person per year)	Di Bao poverty line (yuan per person per year)	Di Bao participation rate (percent of population)	Di Bao payments per recipient (yuan per person per year)
Beijing	13,357	3,480	2.53	535.20
Tianjin	9,789	2,892	6.26	239.88
Shijiazhuang	8,001	2,460	3.29	162.76
Taiyuan	7,855	2,052	2.49	187.16
Huhehaote	7,441	2,160	1.08	260.72
Shenyang	6,345	2,460	4.74	249.51
Dalian	7,835	3,312	3.67	288.75
Chuangchun	7,380	2,028	4.40	146.80
Harbin	6,812	2,400	5.15	239.03
Shanghai	13,767	3,480	6.41	353.98
Nanjing	11,557	2,880	2.66	320.67
Hangzhou	14,882	3,420	0.65	549.09
Ningbo	15,846	3,120	2.42	596.35
Hefei	8,211	2,520	5.66	179.62
Fuzhou	10,452	2,520	0.93	213.97
Xiamen	14,615	3,480	2.13	245.90
Nanchang	7,227	1,980	4.44	153.10
Jinan	8,597	2,496	4.39	284.37
Qingdao	9,235	2,760	1.59	372.01
Zhengzhou	7,732	2,400	1.33	260.37
Wuhan	8,410	2,640	5.59	244.03
Changsha	10,770	2,400	6.02	212.28
Guangzhou	14,039	3,600	1.31	623.32
Shenzhen	26,036	3,600	1.08	497.90
Nanning	7,573	2,280	3.66	85.26
Haikou	8,039	2,652	1.58	139.33
Chongqing	6,007	2,220	12.13	236.99
Chengdu	9,701	2,136	1.84	182.13
Guiyang	7,521	1,872	6.20	206.62
Kunming	7,231	2,280	26.81	155.91
Xian	7,901	2,160	4.08	240.90
Lanzhou	6,895	2,064	5.08	232.62
Xining	7,505	1,860	3.92	165.51
Yinchuan	7,515	2,040	6.09	179.06
Wulumuqi	8,351	1,872	1.87	215.72
Sample Mean	9,951	2,715	3.91	270.19

Source: Mean income, Di Bao participation rate, and Di Bao payments per recipient are calculated from the UHSS conducted by China's NBS; Di Bao poverty line is from administrative records of the Di Bao program (see Section III).

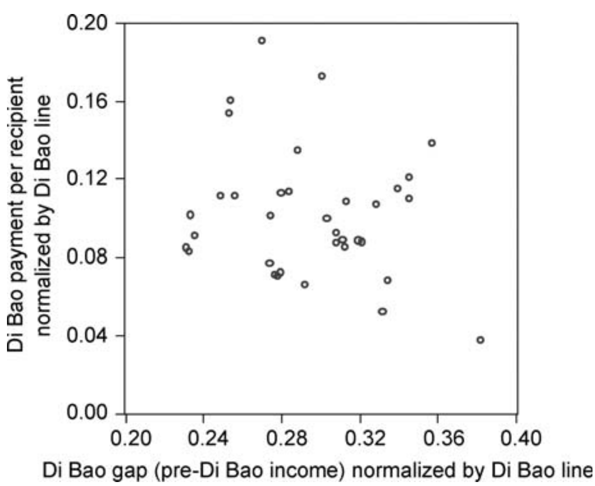
income net of Di Bao payments should be used. Net income is the obvious choice only if measurement errors are ignored. Given that gross income is obtained from a single question on income, it is unclear whether all income sources are properly accounted for in household responses. And the problems in measuring net income are compounded by the likely measurement errors in self-reported transfer receipts from Di Bao. Under these conditions, subtracting mean Di Bao spending at the city level from mean reported gross income may actually add to the bias in estimating the income effect on spending due to measurement errors. The following analysis, which tried both net income and gross income, found that the choice made negligible difference (given the size of Di Bao payments). The city-level results reported in Sections III and IV use gross income.

III. Cross-city Evidence for the Di Bao Program

The survey-based incomes and recorded Di Bao payments do not suggest that the program is working in practice as its design intended. This is evident in figure 1, which compares the estimated Di Bao gaps (distance below the Di Bao poverty line as a proportion of the line) with Di Bao spending across municipalities (also normalized by the Di Bao poverty line). If the program worked as designed and incomes were measured accurately, there should be a perfect positive linear relationship; instead there is a small negative correlation ($r = -0.20$). However, there is undoubtedly considerable noise due to measurement errors both in the estimated Di Bao gaps and in Di Bao spending based on self-reported receipts.

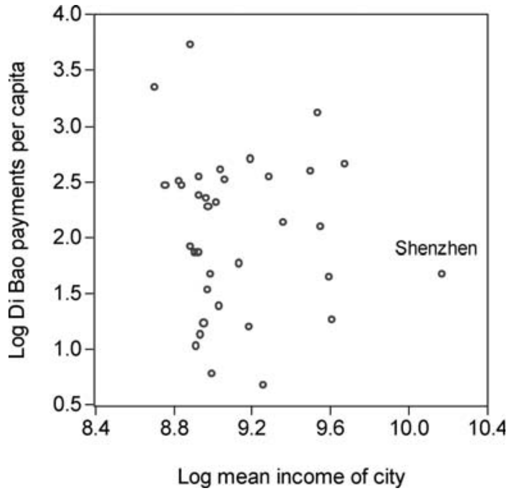
The model in Section I showed that if the program worked in practice as its design intended, then the income effect on program spending would be the net outcome of two opposing effects: the needs effect (whereby poorer municipalities have a greater poverty problem to be addressed) and the resources effect (whereby poorer municipalities have fewer resources for covering their share of the cost). The relative strength of these two effects depends on design of the

Figure 1. Di Bao Gaps against Payments



Source: Author's calculations based on data from China's MOCA and NBS.

FIGURE 2. Di Bao Payments Per Capita against Mean Income, 35 Main Urban Areas of China



Source: Author's calculations based on data from China's MOCA and NBS.

program and on the objectives of local agents. Because the program does not appear to be working as intended, there may be other sources of municipal income effects on program spending, such as differences in administrative capabilities or an income effect on the locally optimal level of redistribution (for example, under certain conditions poorer provinces will be less effective in targeting their poor; Ravallion 1999). A richer set of potential covariates for Di Bao participation using the micro-data will be introduced later (Section V), but for now the analysis focusses on the intercity relationship between program spending and mean income.

Considering the bivariate relationship first, across the 35 cities the regression coefficient of log Di Bao spending per capita on log mean income is -0.220, but it is not significantly different from zero ($t = -0.66$).[15] Figure 2 plots the data. (The correlation coefficient is -0.098.) Dropping the richest city, Shenzhen, the estimated income elasticity falls to -0.150 ($t = -0.31$). There is also a strong positive income effect on Di Bao expenditure per recipient, which has an elasticity of about unity to city income; the regression coefficient of the log Di Bao payment per recipient on log mean income of the city is 0.977 ($t = 5.18$).

In theory, Di Bao spending should also vary according to the program poverty line and differences in the distribution of incomes (Section I). To allow for distributional effects, the standard deviation of incomes within each municipality is used.[16] When a cubic in log Z was initially used, the higher-order

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

16. With only 35 observations there are limits to how many distributional parameters can be allowed for. The coefficient of variation was also tried, but the standard deviation gave a better fit.

terms were individually and jointly insignificant (probability values around 0.5), so the choice became the following regression of log Di Bao spending per capita (S) on log mean income, the standard deviation (SD), and the log Di Bao poverty line:[17]

$$\ln S_j = \underset{(1.58)}{9.443} - \underset{(-2.63)}{2.386} \ln \overline{Y}_j + \underset{(2.15)}{0.113}\mathrm{SD}_j + \underset{(2.42)}{1.720} \ln Z_j + \hat{\varepsilon}_j \tag{11}$$

$$R^2 = 0.147; n = 35.$$

(The estimates changed very little on dropping Shenzhen.)

Equation (11) suggests the presence of both the needs effect (a lower mean income and more unequal distribution generate higher spending at a given Di Bao poverty line) and the resources effect (through the choice of the line). Recalling the theoretical analysis in Section I, the total income elasticity of spending combines three effects: a direct needs effect, a distributional effect (an effect through the variance of incomes), and a resources effect (through the Di Bao poverty 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 mean income and the Di Bao poverty line:

$$\ln S_j = \underset{(-0.13)}{-0.468} - \underset{(1.89)}{0.925} \ln \overline{Y}_j + \underset{(2.06)}{1.401} \ln Z_j + \hat{\varepsilon}_j \tag{12}$$

$$R^2 = 0.075; n = 35.$$

On estimating a similar specification for log Di Bao payments per recipient (S/P, where P is the Di Bao participation rate), SD was insignificant ($t = 0.27$), so it was dropped giving

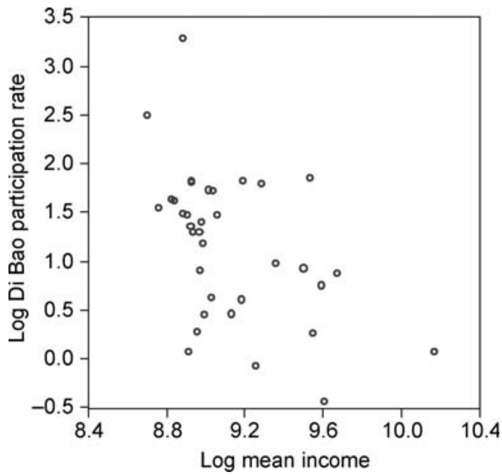
$$\ln(S_j/P_j) = \underset{(-3.59)}{-6.571} + \underset{(2.46)}{0.488} \ln \overline{Y}_j + \underset{(3.43)}{0.971} \ln Z_j + \hat{\varepsilon}_j \tag{13}$$

$$R^2 = 0.568; n = 35.$$

The income effect switches sign from equations (12) to (13). This clearly stems from a negative income effect on Di Bao participation. The estimated elasticity of the 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

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

FIGURE 3. The Municipal Income Effect on Di Bao Participation



Source: Author's calculations.

(in absolute value) when controlling for the Di Bao poverty line; the income elasticity of participation then rises to -1.413 ($t = -3.31$).

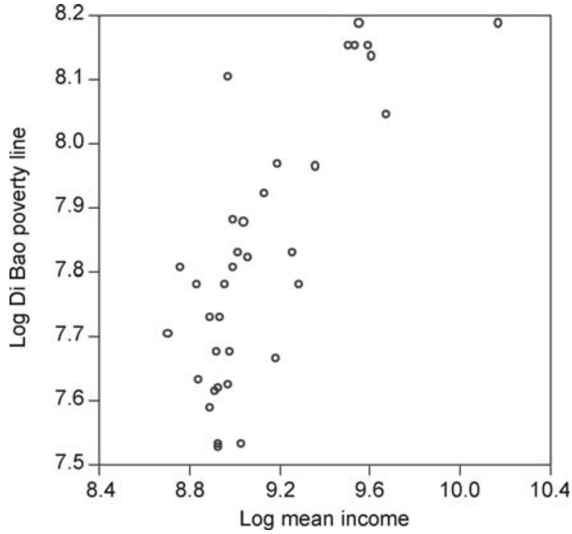
There is also a strong income effect on the Di Bao poverty line. The regression coefficient of the log Di Bao line on log mean income is 0.503, which is not only significantly different from zero at the 1 percent level ($t = 6.92$) but also significantly less than unity ($t = 6.84$). Figure 4 gives the scatter plot. Dropping Shenzhen, the income elasticity is 0.579 ($t = 8.36$).

Thus the small total income effect on spending is the outcome of a negative needs effect at a given Di Bao poverty line (an elasticity of about -0.9) and a positive resources effect operating through the local choice of a line (an elasticity of $0.704 = 1.401*0.503$, using equation (12)). On balance, half the income elasticity of Di Bao payments per recipient in equation (13) is attributable to the positive income elasticity of the lines.[18]

These regressions assume homogeneity in city size. Against this may be fixed administrative costs, yielding scale economies of city size, or congestion effects on the administrative capabilities, yielding diseconomies. While larger cities 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 Di Bao 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 Di Bao poverty line

18. The half is calculated as 0.971*0.503/0.977 (recalling the regression coefficient of the log Di Bao payment per recipient on log mean income is 0.977).

FIGURE 4. Di Bao Lines against Mean Incomes



Source: Author's calculations.

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.

The above results are based on the Di Bao payments recorded in the UHSS. As was clear from figure 1, there are large gaps between the observed levels of Di Bao receipts in the UHSS and the measured poverty gaps. This undoubtedly reflects both errors of targeting in the program's implementation and measurement errors. It is of interest to compare the regressions for recorded Di Bao spending above with the results expected if the program worked as intended and the measurement errors could be treated as white noise. Using the survey-based Di Bao gaps to estimate equation (1), the analogous results to equations (11) and (12) are[19]

$$\text{(14a)} \qquad \ln \hat{C}_j = \underset{(2.91)}{11.753} - \underset{(-5.06)}{2.974} \ln \overline{Y}_j + \underset{(2.61)}{0.094}\text{SD}_j + \underset{(4.73)}{2.374} \ln Z_j + \hat{\varepsilon}_j$$

$$R^2 = 0.486$$

$$\text{(14b)} \qquad \ln \hat{C}_j = \underset{(1.11)}{3.561} - \underset{(-4.37)}{1.761} \ln \overline{Y}_j + \underset{(3.76)}{2.089} \ln Z_j + \hat{\varepsilon}_j$$

$$R^2 = 0.364.$$

19. Squared and cubed terms in log Z were tried, but found to be (highly) insignificant.

Here $\hat{C}_j$ is the cost of filling the Di Bao gap based on income net of the program. On balance (factoring in the income effect on the Di Bao poverty line) the total income elasticity is negative and significant (-0.710, $t = -2.95$). The income gradient in the Di Bao gaps is larger than for recorded Di Bao payments.

These regressions imply that if the program had in fact filled the Di Bao gaps as intended, there would have been a negative income gradient, even allowing for positive income effect on the Di Bao eligibility thresholds. The needs effect would have dominated. This suggests that the ways in which the program in practice differed from its intended (theoretical) ideal acted to diminish its efficacy in reaching poor areas by enhancing the relative importance of the resources effect on spending.

However, caution should be exercised in interpreting regressions (11)–(14). The errors in measuring Di Bao spending based on self-reported Di Bao receipts in the UHSS will attenuate the income gradient if poor respondents tend to understate their true Di Bao receipts. And income measurement errors still influence the results (in all these regressions). The net bias is unclear. If mean income is over- (under-) estimated, the poverty gap is likely to be over- (under-) estimated, suggesting that equations (14a) and (14b) overestimate the true income gradient. However, measurement errors in the survey-based data on municipal incomes are likely to create an attenuation bias in the income elasticities of both the Di Bao gaps and poverty line.

One check for bias due to income measurement errors is to assume that these errors do not alter the income ranking of cities and that the income rank has no independent effect on spending (and so can be excluded from the regression for spending). Under these assumptions, the rank can be used as the instrumental variable for measured income. On doing so, the income elasticity of spending rises (becomes more negative). For example, the instrumental variables estimator for equation (12) is[20]

$$\ln S_j = \underset{(-0.16)}{-0.610} - \underset{(2.08)}{1.564} \ln \overline{Y}_j + \underset{(2.36)}{2.1641} \ln Z_j + \hat{\varepsilon}_j \tag{15}$$

$$R^2 = 0.043; n = 35.$$

The instrumental variables estimator for the income elasticity of the Di Bao poverty line rises slightly to 0.530 ($t = 7.27$). On balance, the total income elasticity of spending rises to -0.416 (from -0.220), but is still not significantly different from zero ($t = -0.97$). Other results were similarly robust to using income rank as the instrumental variable. Bias will remain to the extent that income measurement errors affect the rank order of cities by income.

20. The first stage regression (of $\ln \overline{Y}_j$ on the income rank) had an R^2 of 0.81.

There is another source of bias in the regressions reported in this section, due to omitted intercity differences in the cost of living. Consider the reduced form income elasticity of Di Bao spending; let the true income elasticity be δ_1 in

$$\ln(S_j/\text{COL}_j) = \delta_0 + \delta_1 \ln(\overline{Y}_j/\text{COL}_j) + \nu_j \tag{16}$$

where COL_j is the latent cost of living index for city j. Instead, $\ln S_j = \delta_0 + \delta_1 \ln \overline{Y}_j + \mu_j$, where $\mu_j = (1 - \delta_1)\ln\text{COL}_j + \nu_j$. The ordinary least squares estimate of δ_1 is $\hat{\delta}_1 = \hat{\gamma} + (1 - \hat{\gamma})\delta_1$, where $\hat{\gamma}$ is the regression coefficient of $\ln \text{COL}_j$ on $\ln \overline{Y}_j$. The bias goes to zero only as δ_1 goes to unity or as 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 indexes estimated by Brandt and Holz (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 ordinary least squares elasticity of the Brandt and Holz urban cost of living index across provinces to mean (nominal) income across the 35 cities studied here is 0.213 ($t = 6.44$). Deflating both Di Bao spending and mean incomes by the Brandt and Holz index shows 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 ($t = -1.12$). Re-estimating equations (11) and (12) using the Brandt and Holz deflators yields:

$$\begin{aligned}\ln(S_j/\text{COL}_j) = \underset{(1.22)}{9.428} - \underset{(-2.37)}{2.357}\ln(\bar{Y}_j/\text{COL}_j) + \underset{(1.79)}{0.117}(\text{SD}_j/\text{COL}_j)\\ + \underset{(2.69)}{1.682}\ln(Z_j/\text{COL}_j) + \hat{\varepsilon}_j\end{aligned} \tag{17a}$$

$$R^2 = 0.152.$$

$$\ln(S_j/\text{COL}_j) = \underset{(0.05)}{0.260} - \underset{(-2.06)}{1.035}\ln(\bar{Y}_j/\text{COL}_j) + \underset{(2.26)}{1.433}\ln(Z_j/\text{COL}_j) + \hat{\varepsilon}_j \tag{17b}$$

$$R^2 = 0.095.$$

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

Ignoring the cost of living differences probably leads to an overestimation of the true real income gradient of the Di Bao poverty lines, given that the cost of living is positively correlated with mean income. Using the Brandt and Holz index for the city's province as the deflator for each city gives an elasticity of real Di Bao line to mean real income of 0.384 ($t = 4.40$). The difference is not large; the income elasticity of the Di Bao line falls from about 0.50 to 0.37. Even if the true income gradient of the cost of living was 50 percent higher than implied by the Brandt and Holz deflators (elasticity of the Brandt and Holz index to mean income 0.32 rather than 0.21), the income elasticity of the Di Bao line would still be 0.27. The true income gradient of the cost of living would have to be more than double that implied by the Brandt and Holz deflators to yield zero real income gradient of the Di Bao lines.

Allowing for cost of living differences across cities will probably also yield a higher (real) income gradient in Di Bao participation. That will be the case if the cost of living has a (positive) income elasticity less than unity (so that cities are not re-ranked in terms of incomes when adjusted for cost of living differences).[21] Again, the provincial cost of living indexes estimated by Brandt and Holz provide a clue to the extent of the bias. The indexes give an elasticity of Di Bao participation to mean income rises of -1.410 ($t = 3.65$) (instead of -1.197 using the nominal data). The Brandt and Holz deflators suggest an income elasticity of Di Bao payments per recipient of 0.925 ($t = 4.18$), slightly lower than the unadjusted estimate of 0.977.

In summary, the above results suggest that both the needs and resources effects are present, but are roughly offsetting. 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 Di Bao line. The resources effect is strong enough to roughly cancel out the needs effect—largely neutralizing the program's ability to reach poor municipalities.

IV. Impacts on Poverty

Despite the program's aim of eliminating urban poverty, the overall impact appears to be modest. In the same sample survey used here, Chen, Ravallion, and Wang (2006) find that the poverty-gap index, based on income net of Di Bao receipts, is 2.28 percent; adding Di Bao payments causes it to fall to only 2.06 percent.[22] (Among participants only the corresponding values are 19.92 and 14.23 percent; the higher index for participants reflects the program's targeting to the poor.) The mean poverty gap as a proportion of the Di Bao poverty lines (as given by the poverty-gap index divided by the headcount index) fell from 0.296 to 0.284.

21. To see why, suppose that the true income elasticity of the Di Bao participation rate is γ_1 in $\ln P_j = \gamma_0 + \gamma_1 \ln(\overline{Y}_j/COL_j) + \nu_j$, while the estimated regression is $\ln\bar{P}_j = \gamma_0 + \gamma_1 \ln\overline{Y}_j + \mu_j$, where $\mu_j = -\gamma_1 \ln COL_j + \nu_j$. The ordinary least squares estimate of γ_1 converges in large samples to $\gamma_1 (1 - \delta)$, where δ is the elasticity of COL_j to $\overline{Y}_j$. Thus γ_1 is underestimated given that $1 > \delta > 0$.

22. The poverty-gap index is the mean distance below the poverty line as a proportion of the line (where the mean is taken over the whole population, counting the nonpoor as having zero poverty gaps.) The national value of the index is thus the population-weighted mean of C_j/Z_j.

The scheme is underfunded relative to its aim; the population-weighted mean of the Di Bao payment (per recipient) as a proportion of the Di Bao poverty line is 0.108—slightly more than one-third of the aggregate Di Bao gap. Furthermore, the impact on poverty fell well short of the potential, given the budget outlay. These calculations imply that if all the payments made under the program had gone to the Di Bao poor, the aggregate poverty gap would have fallen by 36 percent (= 0.108/0.296), instead of the actual decline of only 4 percent (= 1−0.284/0.296). The scheme has clearly fallen well short of its potential.

What role has the program's decentralized eligibility played in this weak overall performance against poverty? In particular, how much greater would the program's impact on poverty have been if all the cities had used the same poverty line, set at a level that would have entailed the same aggregate level of public spending? Section III studied the relationship between program spending and the Di Bao line; for notational brevity the empirical relationship can be summarized by a function $S_j(Z_j)$ that gives the level of program spending in city j when Z_j is the local Di Bao poverty line. This assumes that the function $S_j(\cdot)$ remains the same for each j when a single national poverty line is imposed. In other words the municipalities behave the same way; all that changes is the poverty line.

What common poverty line would they confront? Define the budget-neutral national poverty line, Z^*, such that $ES_j(Z^*) = ES_j(Z_j)$. Thus, given the behavior of municipalities, the aggregate spending at Z^* is the same as under the decentralized eligibility thresholds. ($Z^* < \bar{Z}$, the mean poverty line, for $S_j(\cdot)$ strictly concave.) Suppose now that the level of spending S_j yields a poverty impact of $I_j(S_j)$. Define $\Delta_j \equiv I_j(S_j(Z^*) - I_j(S_j(Z_j))$, which is the impact gain (or loss) in j induced by the common poverty line. The contribution of variability in Z_j to the aggregate impact $E[I_j\ (S_j)]$ can then be measured by $E(\Delta_j)$. While $E[I_j(S_j(\bar{Z}) - I_j\ (S_j(Z_j))] > 0$ if I is strictly concave in Z, then $Z^* < \bar{Z}$ implies that $E(\Delta_j)$ could be positive or negative.

To implement this measure, an estimate of the poverty impact of program spending is needed. If the program worked exactly as intended, program spending itself gives the reduction in the aggregate poverty gap due to the program. However, although targeting is excellent, there is still sizeable leakage of benefits to the nonpoor. To allow for this, it is postulated that the program's actual impact on the poverty-gap index depends on program spending as

$$\ln(\mathrm{PG}_{0i}/\mathrm{PG}_{1i}) = \delta_0 + \delta_{1i} \ln S_i + \mu_i. \tag{18}$$

Here PG_{1i} is the post–Di Bao value of the poverty-gap index and PG_{0i}, the pre–Di Bao value. When an augmented version of this specification with controls for the (log) pre–Di Bao poverty measure was tested, it was found to be insignificant. When effects of differences across municipalities in the program's targeting performance were tested using (alternately) the share of Di Bao benefits going to the poor, the normalized share, and the overall concentration index, none was significant (including when interacted with Di Bao spending); this is consistent with the finding of Ravallion (2007) that the program's poverty impacts are uncorrelated with targeting performance across municipalities. When a specification including Di Bao spending per participant and (log) participation rate was tested as separate regressors, the null hypothesis that the coefficients are equal could not be rejected. A squared term in ln$S$ and interaction effects with the pre–Di Bao poverty measure and with the measures of targeting performance also turned out to be insignificant. The only significant effect was an interaction effect between spending and the pre–Di Bao poverty rate, giving the estimated specification:

$$\ln(\mathrm{PG}_{0i}/\mathrm{PG}_{1i}) = -\underset{(-4.38)}{0.067} + (\underset{(10.93)}{0.110} - \underset{(-4.96)}{0.028}\ln \mathrm{PG}_{0i})\ln S_i + \hat{\mu}_i \tag{19}$$

$$R^2 = 0.803.$$

The elasticity of poverty impact with respect to program spending varies from 0.101 to 0.221 with a mean of 0.154 and tends to be lower in poorer municipalities.

How much greater the poverty impact would have been without the variation in Di Bao poverty lines arising from decentralized eligibility can now be quantified. Using equations (11) and (19), the difference between the program's poverty impact ($\ln(\mathrm{PG}_{0i}/\mathrm{PG}_{1i})$) at the mean Di Bao line and its value at the actual line of each municipality is $\hat{\Delta}_i = 1.72(0.11-0.028\ \ln\mathrm{PG}_{0i})\ln(Z^*/Z_i)$. The value of Z^* is 2,666 (compared with a mean Z of 2,715 from table 2).[23] The value of $\hat{\Delta}_i$ varies from -0.06 to 0.06, with a mean of 0.007; by contrast the mean of ln $(\mathrm{PG}_{0i}/\mathrm{PG}_{1i})$ at the actual poverty lines is 0.115.

The upshot of these calculations is that, while the post–Di Bao poverty-gap index would be lower without the variation in Di Bao lines (holding total program spending constant), the extra poverty impact is likely to be very small. The more important reason for the program's low overall impact on poverty is its incomplete coverage of those below the local Di Bao lines and that the Di Bao payments are too low to assure that the Di Bao line is reached. (Recall that the poverty measures reported at the beginning of this section imply that only 12 percent of the aggregate Di Bao gap is being filled by the program.) One can only speculate on the reasons for this weak coverage of the poor. The heavy reliance on self-selection by beneficiaries may have dulled the program's ability to cover all those eligible. Central political economy factors may also

23. The formula is $Z^* = [\bar{S}/M(S_j/Z_j^{1.72})]^{1/1.72}$, where $\bar{S}$ is (population-weighted) mean spending and $M(\cdot)$ denotes the (population-weighted) mean of the term in parentheses.

have played a role, whereby weak coverage of the poor (despite the programs' stated goal) stems from a desire to help other (nonpoor) groups instead.

V. 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 I). The test for horizontal inequity is to see whether the probability of receiving help from the program varies between households that are equally poor but are located in different cities. The test is naturally constrained to the data; the possibility of some unobserved attribute relevant to welfare that is geographically correlated cannot be ruled out. It is important, however, that the test control for observed variables may be correlated with welfare. Excluding these variables from the test would raise the concern that what is being picked up as "horizontal inequity" is really just some geographically associated household characteristic that is correlated with welfare and not fully reflected in measured income.

To assess the extent of this problem, define a dummy variable, $D_i = 1$ if household i receives Di Bao and $D_i = 0$ if not, and let X_i be a vector of relevant "nonincome" factors, including location. The probability of participating in Di Bao is

$$\Pr(D_i = 1) = N[\phi(\bar{Y}_i) + \beta X_i] \tag{20}$$

where N is the standard normal distribution function (so that equation (20) is estimated as a probit) and $\phi(\cdot)$ is a parametric nonlinear function; on experimenting with different functional forms, a quadratic function of $\ln \bar{Y}_i$ provided the best fit.

The X's in equation (20) should include geographic effects, because location can influence living standards independently of other household characteristics, including income. A complete set of municipality effects is allowed by including 34 dummy variables for the 35 cities (Beijing is taken to be the reference).[24] 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 nonincome household characteristics.[25] However, the following discussion uses the results with those controls.

There is a positive correlation between the municipal effects in table 3 (the regression coefficients on the municipal dummy variables) and the Di Bao lines (figure 5). The regression coefficient of the municipal effect on the log Di Bao

24. The Di Bao line is constant within municipalities, so a regression coefficient for the Di Bao line cannot be identified separately from the geographic effects.

25. The coefficients on the extra control variables are omitted to save space. Complete results for the control variables can be found in Chen, Ravallion, and Wang (2006).

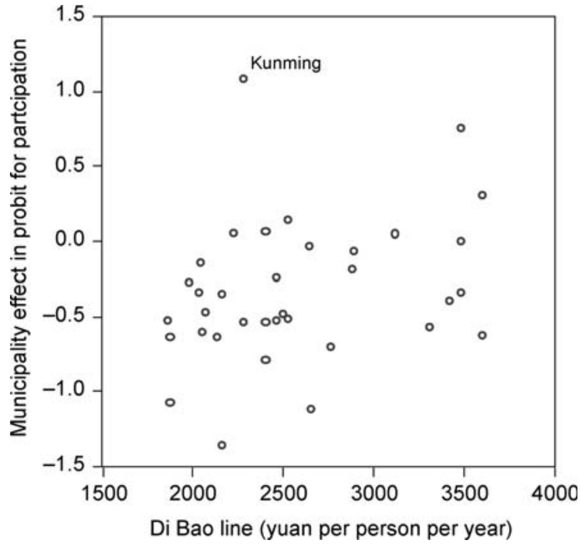
TABLE 3. Probits for Di Bao Participation

	Coefficient	*t*-ratio	Coefficient	*t*-ratio
Log income per capita (net of Di Bao)	0.9661	4.02	0.2725	1.09
Squared log net income per capita	−0.1404	−8.88	−0.0668	−4.08
Controls for household characteristics	No		Yes	
Beijing	Reference		Reference	
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
Number of observations	76,762		76,443	
Pseudo R^2	0.3704		0.4718	

Source: Chen, Ravallion, and Wang 2006.

line is 0.903 ($t = 2.93$). From figure 5 Kunming is an outlier; possibly the survey has oversampled Di Bao 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 location factors being captured by the city effects besides differences in the Di Bao lines; the last regression has an $R^2 = 0.249$.

FIGURE 5. Municipal Income Effect on Participation in the Di Bao Program from Table 3 against the Di Bao Poverty Line



Source: Author's calculations.

The municipal effects could well be picking up omitted, geographically associated, household characteristics.

While the (unconditional) participation rate falls as city income rises (Section III), 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 percent level ($t = 2.52$); when Kunming is dropped the regression coefficient rises to 0.605 ($t = 3.30$).[26]

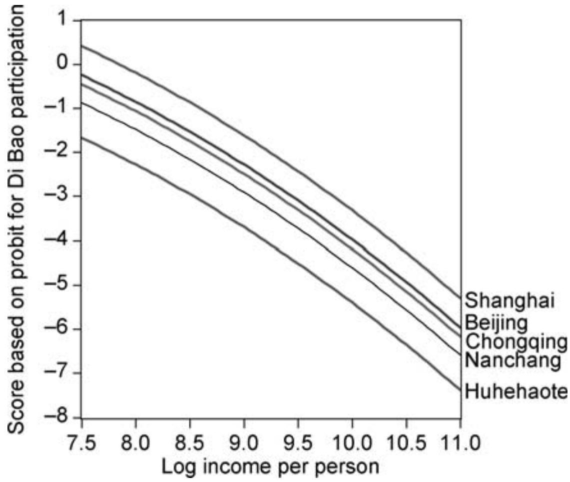
These effects remain reasonably robust when controlling for other "nonincome" factors (the second specification in table 3).[27] With the full set of controls, the regression coefficient of the municipal effects on the log Di Bao line is 0.709 with a t-ratio of 1.99, which is not quite significant at the 5 percent 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 the 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 when asking what

26. As noted, data are not available on the intercity differences in the cost of living. However, by similar reasoning to that in Section II, it can be argued that this data problem will lead to underestimating the real income gradient in the conditional city effects on Di Bao participation.

27. The control variables included the following 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 are available from the author on request.

FIGURE 6. Selected City Effects on Di Bao Participation as a Function of Income



Source: Tables 2 and 3.

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 cities, Nanchang (see table 2). Over the interval in which the scores overlap, the compensating difference in log income is about unity. In other words, a household in Shanghai 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 Di Bao lines. There are no statistically convincing signs that the income effect operates independently of the Di Bao line; on including the Di Bao 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 in the data of horizontal inequity in the program. Holding other observed characteristics constant, people in better-off cities (in terms of mean income) are more likely to receive help from the program.

VI. CONCLUSIONS

Decentralized implementation of an antipoverty 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 be hidden from the center. The literature has pointed to concerns about capture by local elites and migration responses to decentralized antipoverty programs.

This article has focussed 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 informational advantage of decentralization becomes moot. Furthermore, the information needed for setting corrective cost-sharing or interjurisdictional transfers is no less demanding than required for a fully centralized scheme. In short, there is no a priori reason to presume that decentralized implementation dominates centrally imposed eligibility criteria, albeit based on imperfect information.

It is an empirical issue just how much decentralized eligibility attenuates a program's ability to reach the poor nationally, though there has been very little research on that issue. 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. 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 article 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. The local resource constraint greatly diminished the program's ability to reach poor areas—roughly canceling the effect of the intercity differences in need for the program. The overall cross-city income gradient in program spending is still negative, although small and statistically insignificant. The variation in poverty lines associated with the decentralized eligibility criteria attenuated the program's overall poverty impact, but this effect turns out to be quantitatively small relative to the problems of leakage to ineligible households and (more importantly) incomplete coverage of those eligible.

As a consequence of the income effect on the eligibility thresholds, 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 favoring poorer municipalities. The extent of this horizontal inequality suggests that it may create incentives for migration by China's poor. For now, the country's registration system and low Di Bao payments are constraining these incentives for migration. However, looking forward, likely reforms to the registration system (notably to free up the country's labor markets) and efforts to expand outlays and coverage will probably require a more unified, and horizontally equitable, program of social assistance.

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