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Evaluating Workfare When the Work Is Unpleasant

Evidence for India's National Rural Employment Guarantee Scheme

Arthur Alik Lagrange
Martin Ravallion

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Abstract

Prevailing practices in evaluating workfare programs have ignored the disutility of the type of work done, with theoretically ambiguous implications for the impacts on poverty. In the case of India's National Rural Employment Guarantee Scheme, past assessments have relied solely on household consumption per person as the measure of economic welfare. The paper generalizes this measure to allow for the disutility of casual manual work. The new measure is calibrated to the distribution of the preference parameters implied by maximization of an idiosyncratic welfare function assuming that there is no rationing of the available work. The adjustment implies a substantially more "poor-poor" incidence of participation in the scheme than suggested by past methods. However, the overall impacts on poverty are lower, although still positive. The main conclusions are robust to a wide range of alternative parameter values and to allowing for involuntary unemployment using a sample of (self-declared) un-rationed workers.

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Evaluating Workfare When the Work Is Unpleasant:

Evidence for India's National Rural Employment Guarantee Scheme

Arthur Alik Lagrange and Martin Ravallion[1]

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[1] Alik Lagrange is with the University of Toulouse and Ravallion is with the Development Research Group, World Bank. For their comments on an earlier version of this paper the authors thank Rinku Murgai and Dominique van de Walle. They also thank the India Research Group at the Paris School of Economics for providing access to their data while both authors were visiting PSE. Addresses: arthur.alik@midgard.univ-tlse1.fr and mravallion@gmail.com.

1. Introduction

Widespread practice in both the literature and policy discussions has been to use consumption expenditure (or income) as the measure of household economic welfare in assessing the poverty impacts of social programs. An example is found in the research to date on the largest anti-poverty program in India (and probably the largest anywhere in terms of population coverage), namely the Mahatma Gandhi National Rural Employment Guarantee Scheme (NREGS for short). This promises 100 days of work per year per household to all rural households whose adults are willing to do unskilled manual labor at the statutory minimum wage notified for the program. Much has already been written on the scheme, often focusing on its performance in reaching India's rural poor and reducing their poverty as measured by household consumption per person.[2]

However, consumption of commodities cannot be considered a satisfactory metric of welfare in this context, given that it ignores the disutility of the work involved. While many types of work may give disutility, casual manual labor in rural India (whether on a public scheme such as NREGS or in the private sector) is especially hard and unpleasant work by any standards. One typically toils for long hours doing manual labor in the open sun at high temperatures, and with poor facilities and little or no likely job satisfaction. Yet the evaluation methods found in practice attach no disutility to doing such work. Two people with the same real consumption expenditure are deemed to be equally poor even if one of them derives all that consumption from hard grinding toil while the other enjoys leisure time or some relatively pleasant form of work.

Any claim that consumption or income is still an adequate welfare indicator, even if it does not allow for things like the disutility of work, is hard to reconcile with the fact that the ways that consumption aggregates are constructed and how poverty lines are set in practice are typically anchored to some notion of welfare. This might be in a "utility space" or a "capabilities space," but either way it is acknowledged that monetary consumption or income aggregates for households need to be transformed to allow for differences in needs (notably differences in the size and, possibly, composition of the household) and in the prices that are faced, and that the underlying welfare concept should guide how those choices are made in practice. By the same

[2] Dutta et al. (2012a) provides an assessment. Also see the discussions in Jha et al. (2009, 2011), Gaiha (1997), Bhalla (2011), Imbert and Papp (2011).

reasoning, if certain types of work are deemed to give significant negative weight in our assessments of welfare then we cannot justify ignoring that fact when one assesses poverty, for the purpose of deciding if a program such as workfare reaches "poor" people and how much it reduces their poverty.

Indeed, the fact that the work involved gives disutility is one reason why workfare programs have long been used to fight poverty, in both rich and poor countries.[3] The disutility of work helps assure that only those in true need would be willing to do such work. So it can be argued that ignoring this fact in evaluating such a program entails an inconsistency between the rationale for the intervention and the way its performance is assessed.

The literature on poverty in India has long emphasized the link with casual manual labor and the real wage rate for that work.[4] This is seen to be mainly driven by the strong correlation between rural landlessness and poverty, such that the rural poor are more likely to depend on agricultural labor. This is illustrated by Figure 1, which gives the non-parametric regression function of the participation rate in casual manual labor in rural India against the percentile of household consumption per person; the regression allowed for state effects.[5] We see a marked decline in the average participation rate from almost 50% for the poorest percentile to zero for the richest.

The correlation in Figure 1 has an important implication for evaluations of the impacts of a program such as NREGS. It is plain that, for any given participant, we will tend to over-estimate the benefits of the program by ignoring the disutility of doing the kind of work that NREGS provides. However, that does not imply that we will under-estimate the poverty impact of the scheme, given what we see in Figure 1. To the extent that NREGS participants tend to come from households that already do casual manual labor, the correlation in Figure 1 implies that ignoring the disutility of doing casual manual labor will lead one to understate how well

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[3] Workfare has been widely used in crises and by countries at all stages of development. Famously, workfare programs were a key element of the New Deal introduced by US President Franklin D. Roosevelt in 1933 in response to the Great Depression. They were also a key element of the Famine Codes introduced in British India around 1880 and have continued to play an important role to this day in the sub-continent. Relief work programs have helped in responding to, and preventing, famines in Sub-Saharan Africa.

[4] See, for example, Bardhan (1984), van de Walle (1985), Datt and Ravallion (1998), Deaton and Drèze (2002).

[5] The estimation used the partial linear regression routine, PLREG, in Stata (Lokshin, 2006). The state effects entered as additive dummy variables.

targeted such a program is to poor people, who will be even poorer (in terms of welfare) than their consumption suggests. And some participants who are not considered poor when the disutility of the type of work they do is ignored will now be seen to be poor.

The upshot of these observations is that the implications for assessments of the performance of a workfare scheme in reducing poverty are theoretically ambiguous. While ignoring the disutility of work will tend to overstate the welfare gains to the given set of participants it will understate targeting performance. Which of these two effects dominates will determine how the gains from the program are distributed across the population and (in combination with how the chosen poverty measure weights gains at different levels of living) whether or not the poverty impacts are underestimated by standard methods that ignore the disutility of work.

This paper examines the sensitivity of poverty and inequality measures and assessments of the performance of NREGS to the fact that the implicit welfare indicator ignores the disutility of work. We only allow for the disutility of casual manual wage labor. There are, of course, other types of work in this setting. The main alternative to supplying casual manual labor (often for work on another farm) is working on one's own farm. We treat this as a very different form of work that gives little disutility to the farmer, at least relative to casual wage work. Indeed, own-farm work may well give personal satisfaction that is more than enough to outweigh any disutility of the physical labor involved. We also assume that permanent work in this setting (such as working for the government or in a formal-sector enterprise) has very different welfare consequences. Here too there is likely to be significant job satisfaction. Indeed, studies of subjective welfare typically find that a regular job is a direct source of personal satisfaction, with a positive effect on perceived happiness or satisfaction with life.[6] Although we do not know of any supportive evidence, it would seem a plausible assumption that casual manual wage labor in rural India provides little or no intrinsic job satisfaction; the overwhelming direct welfare effect is negative—to be balanced against the positive value of the gain in earnings, as in the classic formulation of the work-leisure choice problem. We comment on the likely direction of bias in our main results if other (non-casual non-manual) work gives disutility.

[6] For an overview of the evidence on this point see World Bank (2012).

We build a simple data-consistent measure of the disutility of casual manual wage labor into welfare measurement and we see how this affects assessments of the targeting performance and poverty impact of NREGS. On allowing for the disutility of casual manual labor supply, we show that poverty and inequality measures for rural India are appreciably higher and that the program performs much better in reaching the poor. However, despite the better targeting, we find that NREGS (in the one state of India for which the required survey data are available) has somewhat lower poverty impacts when we discount the welfare gains to participants.

The following section explains our approach. Section 3 describes our data, while section 4 discusses performance evaluation while section 5 presents the results. Section 6 concludes.

2. Welfare measurement allowing for the disutility of casual manual work

Instead of measuring welfare by household consumption expenditure per capita, C_i, we use <u>adjusted consumption</u> C_i^*, which is re-scaled as:

$$C_i^* = C_i e^{-\alpha(L_i - L^R)} \qquad (C_i > 0, \alpha \geq 0, L_i > 0) \tag{1}$$

Here α is a parameter reflecting the disutility attached to doing casual manual labor, L_i is casual manual labor supply per capita and L^R is a normalizing constant. C_i^* will entail a downward adjustment relative to C_i for "high" supplies of casual labor ($L_i > L^R$) and an upward adjustment for "low" suppliers ($L_i < L^R$). The distributions of C_i and C_i^* are not intrinsically level comparable since L^R can be chosen to attain any ratio of their means. We will set L^R so that the means are automatically balanced ($\overline{C^*} = \overline{C}$) . (We will comment later on the differences in relative distribution.)

Equation (1) is not, of course, the only way one might adjust consumption for the disutility of work. More complex functional forms could be proposed, allowing (for example) for non-separability between labor supply and log consumption in the log of adjusted consumption. However, as we will soon see, this functional form facilitates calibration of the key preference parameter (α) to the available data.

The implications of this adjustment for measures of poverty and inequality are ambiguous in theory, and will depend on the data, notably how L_i varies with C_i. It is instructive to consider one special case, namely when L_i is strictly decreasing in C_i, as suggested by Figure 1. Measured consumption will be adjusted downward for the poorest, and upward for the richest. There will not be first-order dominance, but all standard poverty measures will increase for poverty lines up to the mean. Standard inequality measures will naturally increase; more precisely, there will be Lorenz curve dominance, with unambiguously higher inequality in the adjusted distribution. Just how much the poverty and inequality measures are affected is (of course) an empirical issue.

The implications for assessments of a workfare scheme's impact on poverty are also ambiguous in theory. As discussed in the introduction, we expect our adjustment for the disutility of casual manual work to reveal better targeting to poor people who are more likely to do this type of work, as provided by NREGS. Against this, the effect on the welfare gains to participants of allowing for the disutility of the work provided to them will go in the opposite direction.

How should one set α? This can be recognized as a familiar normative judgment for making inter-personal comparisons of welfare. For the purpose of making consistent inter-personal comparisons of welfare, we need to impose common preferences, so we need to use one reference value of the preference parameter. In choosing that value we will draw on empirical observations of demand and supply behavior. For this purpose we construct the distribution of α as an idiosyncratic preference parameter under the assumption that each household in our sample maximizes $C_i^* = C_i e^{-\alpha_i(L_i - L^R)}$ (in which the preference parameter now varies across households) subject to a budget constraint:

$$C_i = W_i L_i + C_{0i} \qquad (2)$$

where $W_i (> 0)$ is the household daily wage rate for this type of work and $C_{0i} (\geq 0)$ denotes consumption per capita at zero casual labor supply, which is taken to be exogenous.[7] It is readily verified that when labor supply is chosen optimally (and $C_{0i} > 0$):[8]

$$L_i^* = \frac{W_i - \alpha_i C_{0i}}{\alpha_i W_i} > 0 \text{ if } \frac{W_i}{C_{0i}} > \alpha_i \qquad (3.1)$$

$$L_i^* = 0 \qquad \text{if } \frac{W_i}{C_{0i}} \leq \alpha_i \qquad (3.2)$$

[7] Note that this problem is equivalent to maximizing $\ln C_i - \alpha_i L_i$ subject to (2).

[8] In the limiting case with $C_{0i} = 0$, $L_i^* = 1/\alpha_i$ unless $\alpha_i > 1/L_i$ for all $L_i > 0$ in which case $L_i^* = 0$.

When the supply of casual manual labor is positive, it is decreasing in both α_i and C_{0i}, and increasing in W_i. Equation (3.1) can also be written as: $\alpha_i = W_i/C_i$. The intuition here is that W_i/C_i reveals the preference of the household for this type of work: a household with a high disutility attached to doing this type of work will ask for a high wage rate.

We do not assume that everyone has the same preferences. There are clearly idiosyncratic differences in the disutility attached to doing casual labor, which may reflect personal labor histories, caste, gender and demographic characteristics. A natural choice for the common preference parameter in making inter-personal comparisons of welfare is $\hat{\alpha} = Q_{50}\left(\frac{W_i}{C_i}\right)$, the median of the observed ratio of the wage rate to consumption per capita. However, we will test sensitivity to this choice.

The above formulation assumes that the individual is free to supply any amount of labor to casual work—that there is no involuntary unemployment. This assumption can be questioned; some workers may be unable to get as much work as they would like at the going wage rate. We will use a specially designed survey that allows us to identify a sub-sample of those who are not rationed, to test if this alters our main results.

3. Data

We use two household data sets. The first is the 66th round (July 2009-June 2012) of the Employment Schedule ("Schedule 10") of the Government of India's National Sample Survey (NSS). This dataset includes household characteristics (including demographics, NREGS participation, social groups) and information on household members' education, principal and subsidiary activity and time disposition during the week ended (block 5.3). The questionnaire also includes a block on monthly household expenditures during the last 30 days (block 9). We observe the weekly supply of casual manual work and also the daily wage rate for this type of work during the week ended (in block 5.3). The daily wage rate of a household is defined as its total earnings from casual manual work divided by total number of days spent on such work across all household members during the week ended (status code 41, 42 and 51). Table 1 gives summary statistics on L_i, C_i and W_i.

To facilitate estimation of the net gains to participants and to test the robustness of our results using the NSS, we will also use another household dataset collected in rural areas of the state of Bihar with support from the World Bank. Bihar is India's poorest state by the government's official poverty measures (Dutta et al., 2012a). Two rounds of survey data were collected for 3,000 randomly chosen households from 150 random villages spread across Bihar. The first round was between May and July of 2009 and the second during the same months one year later. A two-stage sampling design was followed, using the 2001 Census list of villages as the sampling frame. Data were collected through several survey instruments, including household surveys and individual surveys, the latter for one adult male and one adult female in each household. Dutta et al. (2012b, Chapter 3) contains a fuller description of the survey design.

In this paper we only report results for the first round of the Bihar survey, which is designed to be representative of rural Bihar. However, we did all our analysis for the second round as well and all qualitative findings reported for Round 1 were found to be robust. For comparison purposes we also provide results for the Bihar sub-sample of the NSS.

The World Bank's Bihar Survey contains similar variables to the NSS data (including on consumption), but provides more detail on participation and other variables related to NREGS.[9] Importantly, the Bihar survey includes reported estimates of forgone work and earnings for NREGS participants. The Bihar Survey contains a block on time spent on casual work during the week ended, with total number of days and incomes for each activity (block 23). Thus we are able to estimate income gains (net of forgone earnings) from NREGS in Bihar, and impacts on poverty. Moreover, we know if household members had enough NREGS working days if they worked on NREGS, or if they did not want to work on the scheme, both during the year ended.

Another attraction of the Bihar Survey is that the questions asked allow us to plausibly identify households who are not rationed in the casual rural labor market. These are identified as the sub-sample who report that they do not want more work on the NREGS than what they have already. Since NREGS pays a higher wage rate (about 10% higher in Bihar) than the casual labor

[9] One difference is that we do not have the split manual/non-manual work in the Bihar survey: we only know if the activity was or was not casual work. This implies higher participation rate in this type of work in the Bihar Survey (21.1%% in the NSS data on rural Bihar versus 39.8% in the Bihar Survey).

market it can be safely assumed that a household who does not desire more work on NREGS is not rationed in the private market.

4. Performance evaluation

By comparing the distributions of unadjusted consumption C_i with adjusted consumption C_i^* we are able to quantify the impact of allowing for the disutility of work on assessments of the program's performance. There are two aspects of performance to focus on. The first is targeting performance. Here we analyze the relationship between the participation rates in NREGS and the position along the distribution of consumption per capita, for both the raw data and using locally weighted regressions.[10] Using the two different welfare measurements, C_i and C_i^*, we estimate f and f^* defined as non-parametric relationships between the participation rate (PR) and the position along the distribution of these two measurements:

$$PR(x) = f\big(F_C(x)\big) \tag{4}$$

and similarly for the adjusted consumption, for which the non-parametric function is denoted f^*. Thus $PR(x)$ is the participation rate observed for a given level of consumption x and $F_C(.)$ is the cumulative distribution function (CDF) of consumption and f is a smooth non-parametric function to be determined empirically.[11] If the program is indeed well targeted in terms of adjusted consumption C^* then we should observe that the function f^* is decreasing for all x.

Second, we study the impact of our adjustment on the gains from the scheme. For this purpose we use household-specific estimates of forgone income for men and women from the Bihar Survey. These are answers to the questions: *"If you were doing some other work instead of this during these days, how many days do you think you would have worked?"* and *"If you were doing some other work instead of this during these days, what wage would you might have earned per day?"* [12] (The NSS does not contain these questions, which were developed for the Bihar survey.) The post-NREGS distribution of consumption is that observed in the data.

[10] We used the method of running-line least-squares smoothing using Cleveland's (1979) tricube weighting function, as programmed in Stata (as the "lowess" command). We use a smoothing parameter of 0.5. We could have used the cross-validated bandwidth instead, but for the essentially graphical purposes of this paper we followed Deaton (1989) in selecting a bandwidth such that gives enough smoothness without losing detail, thus also avoiding the computational burden implied by cross-validated bandwidth selection.

[11] Alternatively we can focus directly on the relationship between *PR* and *x* (rather than *F*(*x*)). However, using *F*(*x*) for the horizontal axis assures an even spread of data points, giving an incidence graph that is less prone to outliers at the extremes.

[12] For further discussion see Dutta et al. (2012b).

Without the adjustment for the disutility of manual labor the pre-NREGS distribution is derived from the post-NREGS distribution simply by subtracting the net gains from the scheme, as given by gross wages less the imputed forgone income as reported by the household. The gain from the scheme is then defined as (in obvious notation) $G_i = C_i^{post} - C_i^{pre}$. The calculation is more complicated for the adjusted consumption, for which the gain is $G_i^* = C_i^{*post} - C_i^{*pre}$ where:

$$C_i^{*j} = C_i^j e^{-\alpha\left(L_i^j - L_j^R\right)} \quad (j\text{=}post,\ pre) \tag{5}$$

We analyze then the relationship between the net gains and the position along the consumption distribution, both original and adjusted, following a similar non-parametric approach described above for participation.

In aggregating these gains we shall use the popular headcount index (H), given by the proportion of the population living in households with mean consumption below the poverty line. However, given that our adjustment for the disutility of work is changing distribution below the line, it is of interest to also look at two “higher-order” measures, for which we use the poverty gap (PG) index, to also reflect the depth of poverty, and the squared poverty gap (SPG) index, which penalizes inequality among the poor, and can thus be interpreted as reflecting the severity of poverty. All three measures are members of the Foster-Greer-Thorbecke (1984) class of additive measures of poverty.

5. Results

Using the NSS data (rural only) and using the median ($Q_{50}\left(\frac{W_i}{C_i}\right)$) as our estimator, we find a disutility parameter $\hat{\alpha}$ of 0.52.[13] We find similar values in the other datasets described above, namely 0.59, 0.52 and 0.57 for respectively NSS Bihar, Bihar Survey sample as a whole and the Bihar Survey for un-rationed households only. Figure 2 shows a kernel estimation of the distribution of W_i/C_i and Table 2 gives corresponding summary statistics for the four datasets.

[13] To help interpret this number, imagine a household that derived its consumption solely from casual manual work. Then a value of 0.5 for W_i/C_i means that 2 days of casual labor were supplied per week per household member, which paid for the weekly consumption of one household member.

In all four datasets the distribution of W_i/C_i is skewed to the right and has a clear mode around 0.5. There are outliers. This supports our use of the median instead of the mean.[14]

We first consider the effects of the adjustment for the disutility of casual manual work on measures of poverty and inequality based on the post-NREGS distributions.[15] Table 3 summarizes the joint distribution of C_i and C_i^*. Given that there is a higher incidence of casual manual work in the poorer segments of the population, it is to be expected that the lower part of the distribution is more impacted by the consumption adjustment. Our adjustment for the disutility of work has an impact on measured poverty and inequality. Figures 3 and 4 show respectively the cumulative distribution functions and the corresponding Lorenz curves.[16] As is evident in Figure 3, we do not have first-order dominance, so the ranking in terms of any standard measure of poverty will depend on the precise measure used and the poverty line (Atkinson, 1987). Poverty measures are higher under our adjustment for the disutility of work up to about the median.

Table 4 gives the impacts of our adjustment on the H, PG and SPG indices for all four data sets. We give results for both the median and the quantile of the 40th percentile. Recall that the distributions are automatically balanced in their means, so here we are measuring the effects on poverty at a given mean, interpretable as the "distributional component" of the poverty measure (Datt and Ravallion, 1992). Notice that the adjusted the H index is actually lower than for unadjusted consumption when using the median as the poverty line. This reverses when we switch to PG and SPG. In the all-India NSS sample, and using the median as the poverty line, the PG index rises from 13.7% to 17.4%, while the SPG index rises from 5.2% to 9.9%. Using a poverty line at the 40th percentile, the SPG index more than doubles from 3.6% to 8.4%. The changes were similar for the other datasets.

Inequality is unambiguously higher after our adjustment for the disutility of work (Figure 4). In order to quantify this increase in inequality, we report in Table 5 the corresponding Gini

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[14] The standard deviation is higher for the Bihar Survey sample as a whole and the sub-sample for un-rationed households only, which can be explained by the fact that we include more heterogeneous types of casual work in the definition of L_i, suggesting a higher variance in wages.

[15] Recall that we can only measure the net gains due to the program using the specially-designed World Bank Bihar survey. Thus we can only derive pre-NREGS consumptions for that dataset.

[16] Here and elsewhere we use household weights (expansion factors) to assure that the sample-based calculations are representative of the population in the base year.

coefficients calculated before and after the adjustment for the disutility of work. For the first implementation (using the whole NSS), the Gini coefficient rises from 31% to 43%, which is a substantial increase. Comparing the Bihar sample of the NSS with the World Bank's Bihar survey sample as a whole, the rise in Gini coefficient is clearly higher for NSS Bihar (+0.14 for NSS Bihar versus +0.5 for World Bank survey sample as a whole). We find less change in measured inequality among the un-rationed households, with a Gini coefficient increasing from 27% to 30%, but this may be explained by the fact that the participation rate in casual work is lower in this sub-sample (around 18% of the un-rationed households reported a valid L_i and W_i, versus 40% in the sample as a whole).[17]

Turning next to assessments of targeting performance, we estimate f^* and f for the NSS data (rural households only) using $\hat{\alpha}$=0.52 as suggested by the above results on C_i/W_i. The result of this estimation is showed in Figure 5 (top left hand-side). For both f^* and f the participation rate decreases as consumption rises. Using the original consumption (without our adjustment) we see that participation rates are lower than average for roughly the richest 50%, but we see no clear sign of better targeting within the poorer half of the distribution ($f(x)$ is quite flat for $x \in [1,50]$). However, after adjusting for the disutility of work, we see much better targeting performance among the poor, particularly for $F_{C_i^*}(x) \in [10,40]$.

We also test for robustness with respect to the choice of $\hat{\alpha}$. For this purpose, we repeat the analysis using several values for $\hat{\alpha}$ (Figure 6). Since the first derivative of the adjustment term $e^{-\hat{\alpha}(L_i-L^R)}$ with respect to $\hat{\alpha}$ is negative for "high" supplier ($-(L_i - L^R)e^{-\hat{\alpha}(L_i-L^R)} < 0$, $\forall L_i > L^R$), we expect to observe a greater impact on targeting performance on the lower part of the distribution when using higher $\hat{\alpha}$ (the lower $e^{-\hat{\alpha}(L_i-L^R)}$ the higher the impact). This is confirmed by Figure 6. The second derivative with respect to $\hat{\alpha}$ is positive ($(L_i - L^R)^2 e^{-\hat{\alpha}(L_i-L^R)} \geq 0$) and we observe consequently a diminishing increase of the impact when increasing $\hat{\alpha}$.

Redoing the same estimation but on the NSS Bihar sample and the Bihar Survey, we find that $f(x)$ is flatter than $f^*(x)$ for the poorer half of the distribution (Figure 5). In the Bihar

[17] Recall the category un-rationed includes also households reporting that they do not want to participate in NREGS works.

Survey, the adjusted version shows good targeting performance on the entire wealth distribution with $\frac{\partial f^*(x)}{\partial x} < 0, \forall x \in [1,100]$.[18] However, testing for robustness with respect to $\hat{\alpha}$, a flat area appears among the 10% poorest. Using NSS Bihar data we also find high targeting performance for $F_{C_i^*}(x) \in [20,40]$, but we also see a deterioration among the poorest 20% $\left(\frac{\partial f^*(x)}{\partial x} \geq 0, \forall x \in [1,20]\right)$.

The definition of L_i is not exactly the same in the NSS and in the World Bank's Bihar surveys. This implies some discrepancies in the impact of the proposed adjustment on targeting performance assessments. Nevertheless, we see consistently better targeting performance among the 50% poorest when using C_i^* instead of C_i, with less impact of the adjustment among the richest 30%.

We test if involuntary unemployment matters by estimating f^* and f for un-rationed households only using the information available in the World Bank's Bihar survey. Redoing our analysis on this subsample, we get an estimated f^* that is clearly steeper around the bottom of the distribution. The participation rate among the poorest is more than double using adjusted consumption. This pattern is robust when changing $\hat{\alpha}$, as observed in Figure 6.

It will be recalled that the above calculations only adjust for the disutility of casual manual wage labor. As we note in the introduction, this is a type of work in this setting that is very likely to yield disutility—far more so than self-employment on one's own farm or regular salaried work. But that is an assumption on our part. If in fact these other forms of work also yield disutility then we expect that the corrected targeting performance will not be as pro-poor as we report above, using only our adjustment for the disutility of casual manual wage work. Given that we will now show that (for Bihar at least) the improvement in measured targeting performance is not great enough to outweigh the reduced benefits of participation in NREGS when we allow for the disutility of the work provided, our main qualitative conclusion concerning the poverty impacts will remain valid.

Using the World Bank's Bihar survey we can also study the distribution of the net gains from the scheme along the distribution of C_i^* and C_i . Figure 7 shows how the mean net gains

[18] This result is qualified when checking for robustness with respect to the choice of $\hat{\alpha}$ as reported in Figure 6.

against pre-NREGS consumption, with and without our adjustments, for various values of α. We see from Figure 7 that the net gains from the scheme are highest for the poorest using un-adjusted consumption, but the impacts are attenuated when we adjust for the disutility of the work provided by the scheme. This effect is not found for the sub-sample of un-rationed households, for whom the difference is attenuated by the lower participation rate, as noted above.

Table 6 gives the impacts of NREGS earnings on poverty for both the population as a whole and for the sub-sample of NREGS participants for the median α. We first give results using a common poverty line, set at the median of the post-NREGS distribution of (un-adjusted) consumption. (Qualitatively similar results were obtained using consumption at the 40th percentile.) We see that the poverty measures (both post-NREGS and pre-NREGS) are generally higher with our adjustment for the disutility of casual manual labor; the only exception is for the headcount index in the population as a whole. The impact estimates (post-NREGS less pre-NREGS) are found to be lower for all three poverty measures after adjusting for the disutility of labor.[19] As implied by Figure 7, poverty impacts are little affected by our adjustment for the disutility of work using the sample of un-rationed households.

These results use the median of the post-NREGS un-adjusted consumption distribution as the poverty line. One can question whether the same poverty line should be used with or without our adjustment for the disutility of work. In effect, this amounts to using the reference casual labor supply in setting the poverty line for the adjusted distribution of consumption. It will be recalled that the reference value was chosen to balance the means of the two distributions. However, this need not accord with the labor supply to casual manual work of people living at or near the median of the post-NREGS un-adjusted consumption distribution. Table 6 also provides the analogous estimates obtained when we use average labor supply of people in a neighborhood of the post-NREGS consumption median. The main results are robust to this change.

6. Conclusions

Workfare schemes typically offer unpleasant work. In the case of India's National Rural Employment Guarantee Scheme the work provided is manual labor, toiling for long hours in the

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[19] Notice also that the impact on the income-gap ratio—namely the mean distance of the poor below the line, as a percentage of the line (i.e., the ratio of the PG index to the headcount index)—is also lower with our adjustment.

open sun. Nobody is likely to enjoy this work, and that is undoubtedly part of the reason that relatively rich people appear to rarely turn up for work on the scheme. Yet, while this "self-targeting" mechanism is a key aspect of the rationale for such schemes in fighting poverty, the fact that the type of work is unpleasant has never (to our knowledge) been used in assessing the welfare of actual or potential participants.

This paper has offered a simple correction for this deficiency in past assessments of the performance of such programs. Our adjustment to measured household consumption to allow for the disutility of casual manual labor involves a single preference parameter that can be readily calibrated to available data assuming that labor supply choices are utility maximizing. We have also proposed a robustness test given the possibility of involuntary unemployment in casual labor markets. The empirical implementation has been for India's NREGS.

The proposed adjustment of the welfare measure for the disutility of casual manual labor entails a marked difference to standard measures of poverty and inequality. The distributional change implies a lower incidence of poverty, but higher measures of its depth and severity; for example, the squared poverty gap index roughly doubles. For rural India as a whole, the Gini index of inequality rises from 0.31 to 0.43.

The adjustment also affects the assessment of targeting performance of NREGS. Whereas the choice between the unadjusted consumption and our adjusted version does not make a significant difference among the 30% richest, the assessed targeting performance is changed appreciably among the poorest half of the distribution when we allow for the disutility of doing casual manual work.

However, allowing for the disutility of work also devalues the benefits to participants. Using survey data for Bihar, we find that this effect dominates the better targeting performance implied by allowing for the disutility of the type of work done. The scheme reaches even poorer people, but that it does less to raise their welfare. On balance the poverty impact of the scheme is lower, representing a decline of 0.8 percentage points in the overall poverty rate in Bihar, as compared to 1.2 points when the disutility of work is ignored.

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Table 1: Summary statistics for L_i, C_i and W_i

	NSS			NSS Bihar			Bihar Survey			Bihar Survey: un-rationed only		
	C_i	L_i	W_i	C_i	L_i	W_i	C_i	L_i	W_i	C_i	L_i	W_i
mean	236	2.4	95	170	2.1	81	171	1.1	76	191	1.0	78
s.d.	205	1.5	48	79	1.3	26	100	0.8	38	103	0.9	41
N	59129	13793	13793	3300	697	697	3000	1201	1194	1014	186	183
min	9	0.1	8	36	0.2	10	13	0.1	1	13	0.1	5
$y(25)$	143	1.3	67	119	1.3	64	109	0.6	60	120	0.5	50
$y(50)$	193	2.0	87	151	1.8	80	149	0.9	70	165	0.7	80
$y(75)$	267	3.2	110	202	2.3	95	202	1.3	100	228	1.3	100
max	14738	7.0	2000	1970	7.0	286	2376	7.0	890	809	7.0	325

Note: W is in rupees per day, calculated as the total wages received for casual manual work divided by the total number of days of such work provide by the household; C is in rupees per person per week, calculated as total household consumption per week divided by the number of people in the household; L is in days per capita, calculated as total number of days of casual manual work divided by household size. $y(p)$ denotes the value of each variable at the p'th percentile.

Table 2: Summary statistics on W_i/C_i

W_i/C_i	mean	s.d.	N	min	$y(10)$	$y(25)$	$y(50)$	$y(75)$	max
NSS all rural India	0.57	0.32	13793	0.03	0.26	0.38	0.52	0.71	16.18
NSS rural Bihar	0.63	0.31	697	0.08	0.28	0.43	0.59	0.77	2.79
Bihar Survey whole sample	0.63	0.41	1194	0.01	0.22	0.34	0.52	0.82	3.98
Bihar Survey un-rationed only	0.63	0.42	183	0.02	0.17	0.31	0.57	0.86	2.61

Table 3: Distribution across quintiles before and after adjustment (%)

(NSS all rural India)

Quintiles of		C_i 1	2	3	4	5	Total
C_i^*	1	8.2	4.4	3.6	2.5	1.3	20.0
	2	10.3	3.5	3.1	2.2	0.9	20.0
	3	1.4	12.0	5.1	0.8	0.7	20.0
	4	0.0	0.0	8.3	11.3	0.4	20.0
	5	0.0	0.0	0.0	3.2	16.8	20.0
	Total	19.9	20.0	20.0	20.0	20.1	100.0

(NSS rural Bihar)

Quintiles of		C_i 1	2	3	4	5	Total
C_i^*	1	7.2	4.6	3.4	3.3	1.6	20.1
	2	8.6	3.9	4.3	2.3	0.9	20.1
	3	4.0	11.3	4.2	0.1	0.3	19.9
	4	0.0	0.0	8.3	11.7	0.1	20.0
	5	0.0	0.0	0.0	2.6	17.4	20.0
	Total	19.8	19.8	20.1	20.0	20.3	100.0

(Bihar survey: whole sample)

Quintiles of		C_i 1	2	3	4	5	Total
C_i^*	1	11.9	3.8	1.7	1.9	0.7	20.0
	2	8.1	5.6	3.7	1.9	0.8	20.0
	3	0.0	10.5	6.3	2.5	0.8	20.1
	4	0.0	0.0	8.4	10.3	1.2	20.0
	5	0.0	0.0	0.0	3.5	16.5	20.0
	Total	20.0	20.0	20.0	20.0	20.0	100.0

(Bihar survey: un-rationed sub-sample)

Quintiles of		C_i 1	2	3	4	5	Total
C_i^*	1	15.1	2.0	1.8	0.9	0.4	20.1
	2	5.1	12.8	1.4	0.7	0.0	20.0
	3	0.0	5.2	14.0	0.7	0.2	20.0
	4	0.0	0.0	2.8	16.6	0.5	19.9
	5	0.0	0.0	0.0	1.2	18.8	20.0
	Total	20.2	19.9	19.9	20.0	19.9	100.0

Table 4: Poverty measures with and without adjustment for the disutility of work

Percent	Median (Q50) of unadjusted consumption as poverty line		Q40 of unadjusted consumption as poverty line	
	Unadjusted consumption	Adjusted consumption	Unadjusted consumption	Adjusted consumption
NSS all rural India				
Headcount index (F(Q(x))	50.0	40.5	40.0	34.6
Poverty gap index	13.7	17.4	10.0	14.7
Squared poverty gap index	5.2	9.9	3.6	8.4
NSS rural Bihar				
Headcount index (F(Q(x))	50.0	34.9	40.0	30.5
Poverty gap index	12.3	15.1	8.9	13.0
Squared poverty gap index	4.2	8.4	2.9	7.1
World Bank Bihar Survey				
Headcount index (F(Q(x))	50.0	47.7	40.0	39.5
Poverty gap index	13.3	17.0.9	9.5	13.3
Squared poverty gap index	4.9	7.7	3.3	5.8
World Bank Bihar Survey (unrationed)				
Headcount index (F(Q(x))	40.6	38.6	31.6	29.9
Poverty gap index	9.9	12.6	6.7	9.4
Squared poverty gap index	3.5	5.5	2.3	4.0

Table 5: Gini Coefficients

	Gini coefficient using original consumption (C_i)	Gini coefficient using adjusted for disutility of work (C_i^*)
NSS	0.31	0.43
NSS Bihar sample	0.24	0.38
World Bank Bihar Survey	0.28	0.33
Bihar using un-rationed sub-sample	0.27	0.30

Table 6: Impacts of NREGS on poverty in Bihar with and without the adjustment for the disutility of work

Percent	Population as a whole			NREGS participants		
	Unadjusted consumption	Adjusted consumption using a common poverty line	Using an adjusted poverty line consistent with average labor supply at the unadjusted line	Unadjusted consumption	Adjusted consumption using a common poverty line	Using an adjusted poverty line consistent with average labor supply at the unadjusted line
Headcount index						
Post-NREGS	50.0	47.7	41.8	56.6	64.2	57.4
Pre-NREGS	51.2	48.5	42.6	60.3	66.4	59.9
Impact (Post minus pre)	-1.2	-0.8	-0.8	-3.7	-2.2	-2.5
Poverty gap index						
Post-NREGS	13.3	17.0	14.3	15.7	23.9	20.4
Pre-NREGS	14.0	17.5	14.7	17.7	25.1	21.6
Impact (Post minus pre)	-0.7	-0.5	-0.4	-2.0	-1.2	-1.2
Squared poverty gap index						
Post-NREGS	4.9	7.7	6.3	5.8	11.2	9.3
Pre-NREGS	5.3	8.0	6.6	7.0	12.1	10.1
Impact (Post minus pre)	-0.4	-0.3	-0.3	-1.2	-0.9	-0.8

Note: The common poverty line is the median for the unadjusted post-NREGS distribution for the population as a whole (135.2 Rupees per capita per week). The adjusted poverty line uses average supply of casual manual labor in a neighborhood of the above median (124.4 Rupees per capita per week, see text).

Figure 1: Participation rate in casual manual work as a function of household consumption per capita

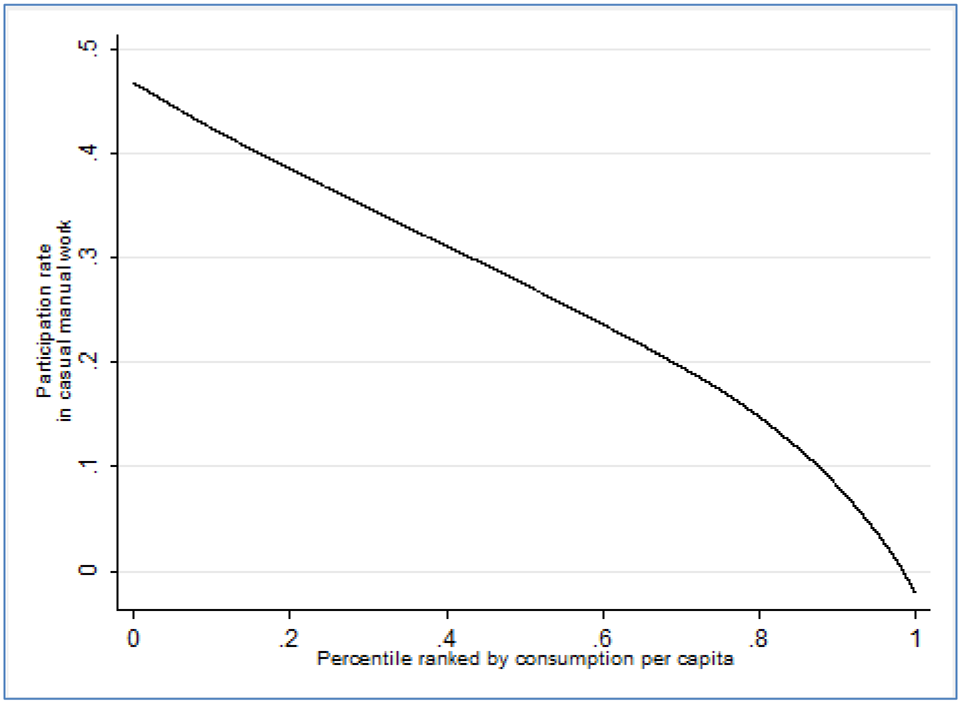


Figure 2: Kernel density estimation of W_i/C_i distribution

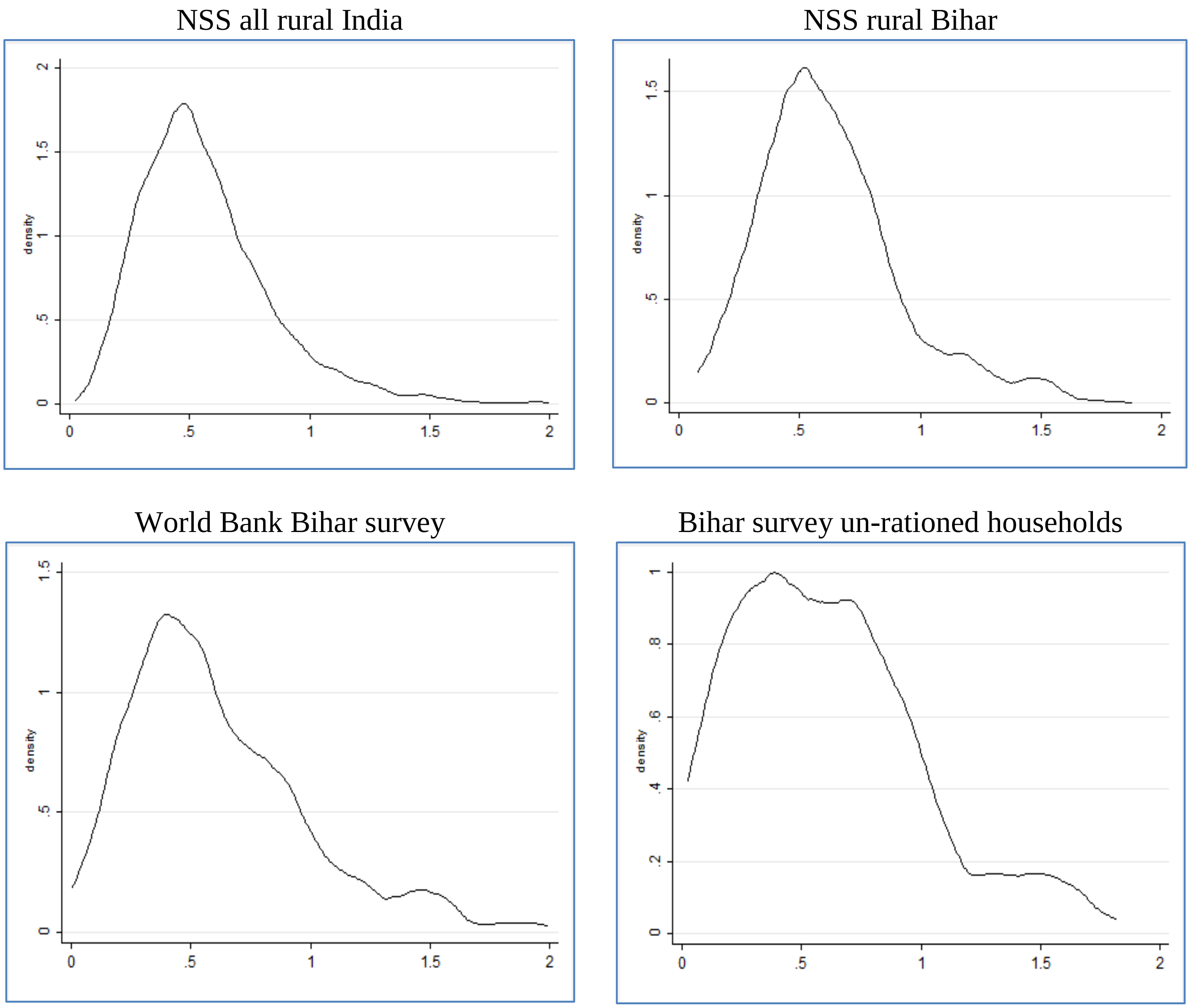


Figure 3: Cumulative Density Functions

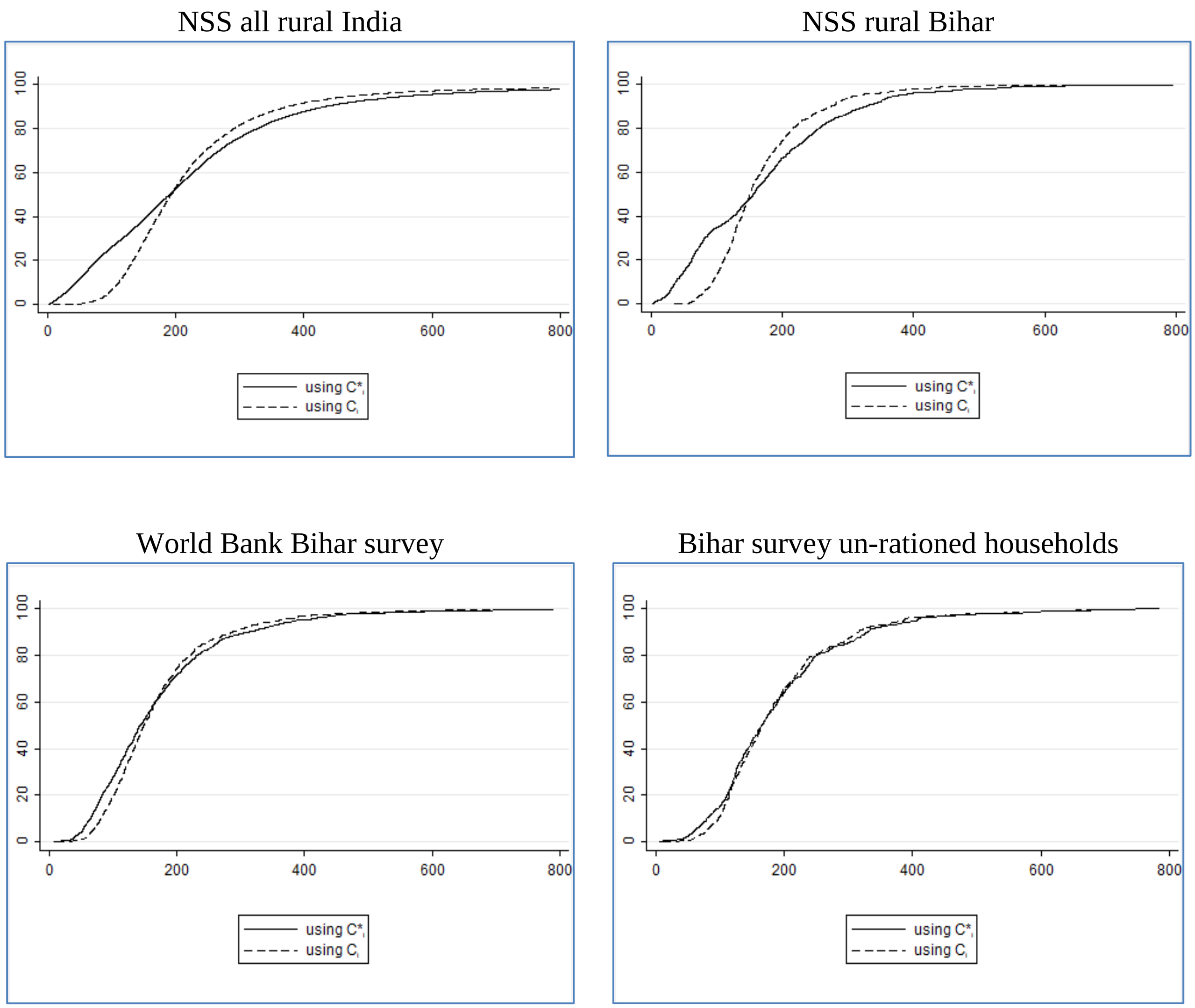


Figure 4: Lorenz Curves

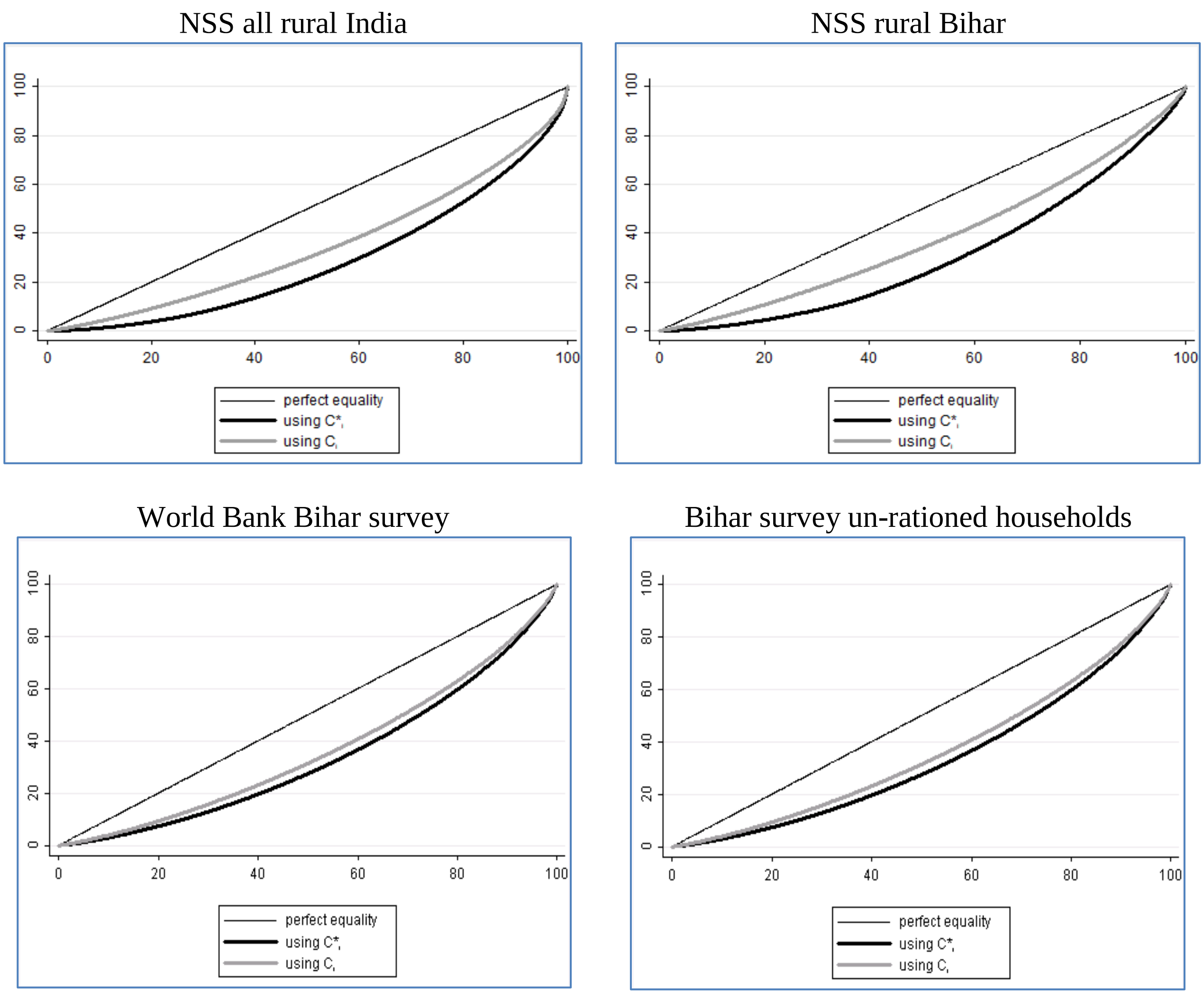


Figure 5: NREGS participation rates

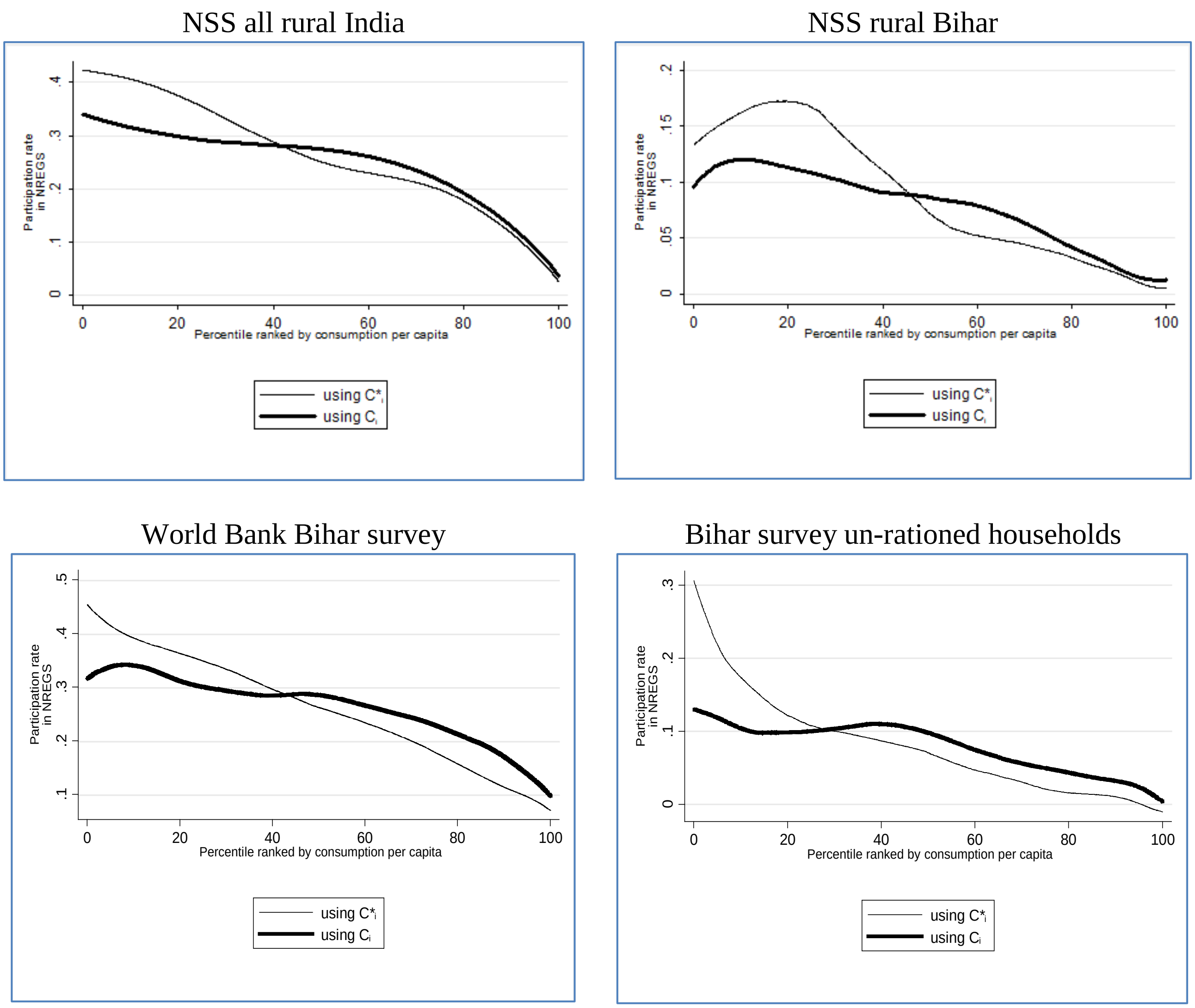


Figure 6: NREGS participation rates for alternative parameter values

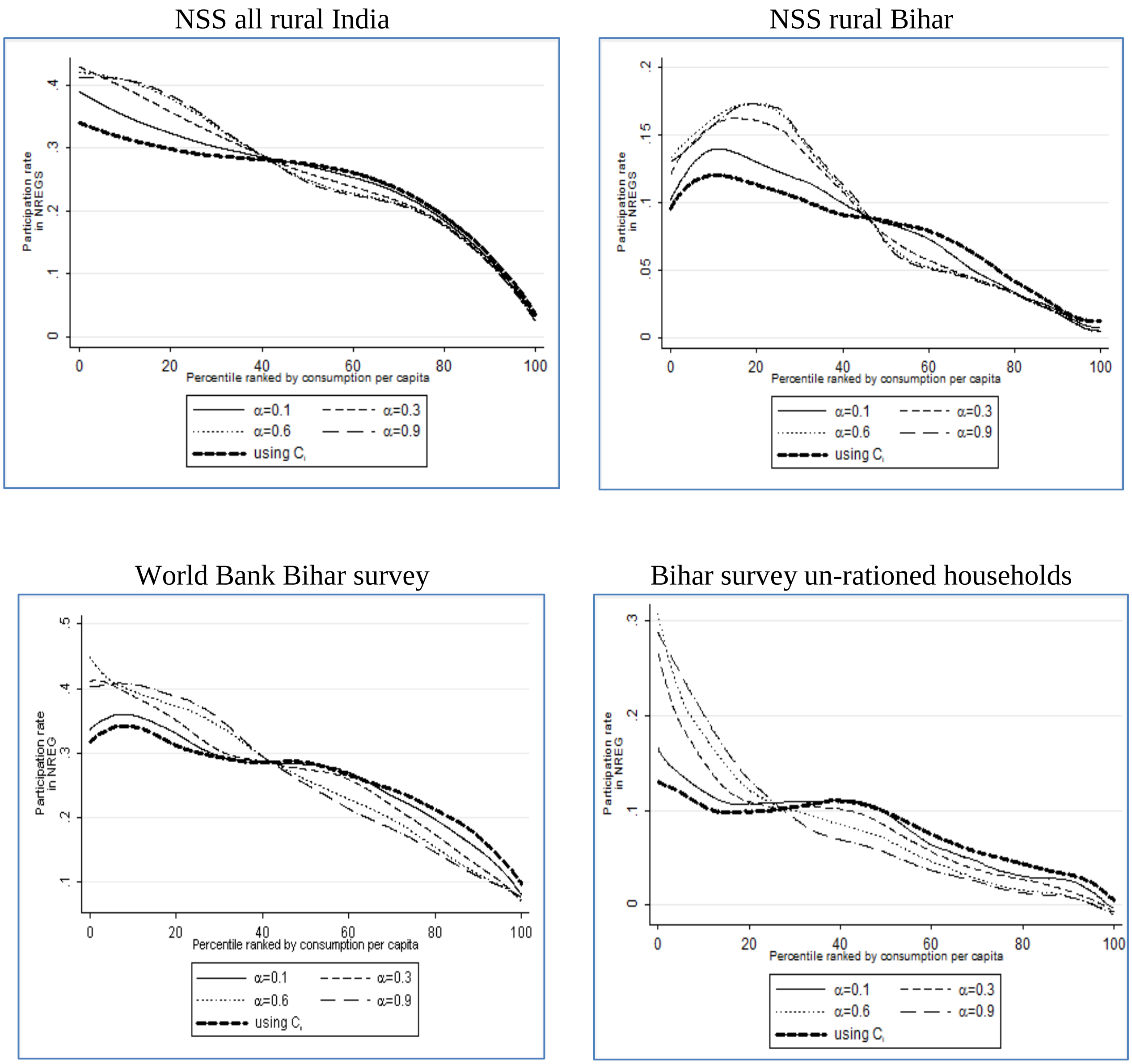
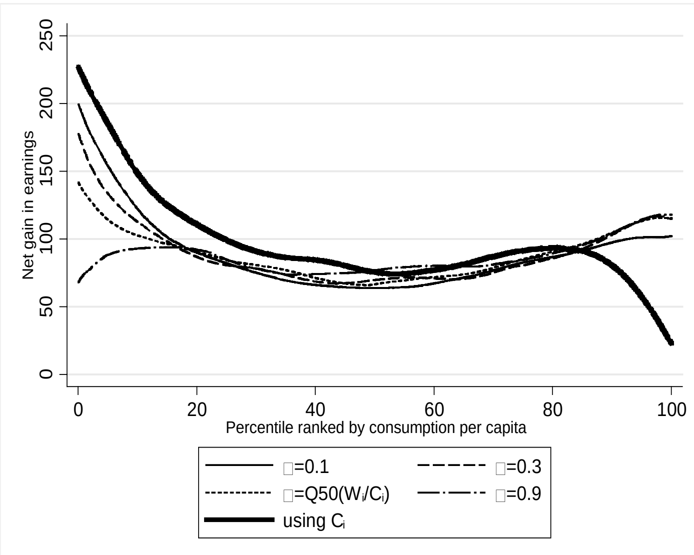


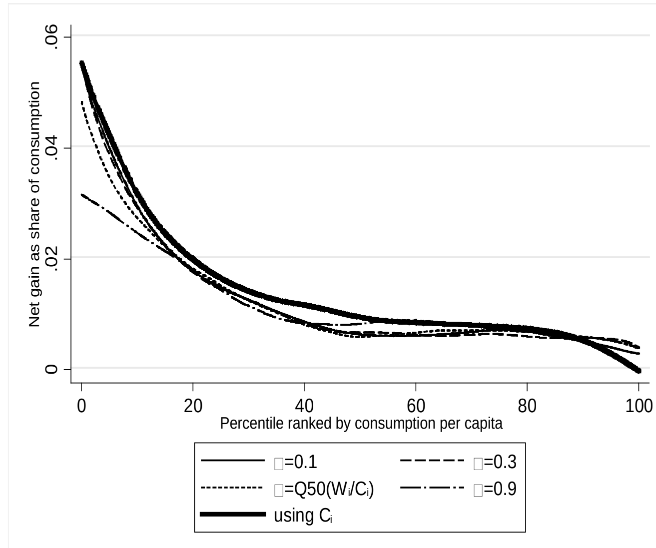
Figure 7: Net gains from NREGS using World Bank Bihar Survey

Sample as a whole

(rupees per year)

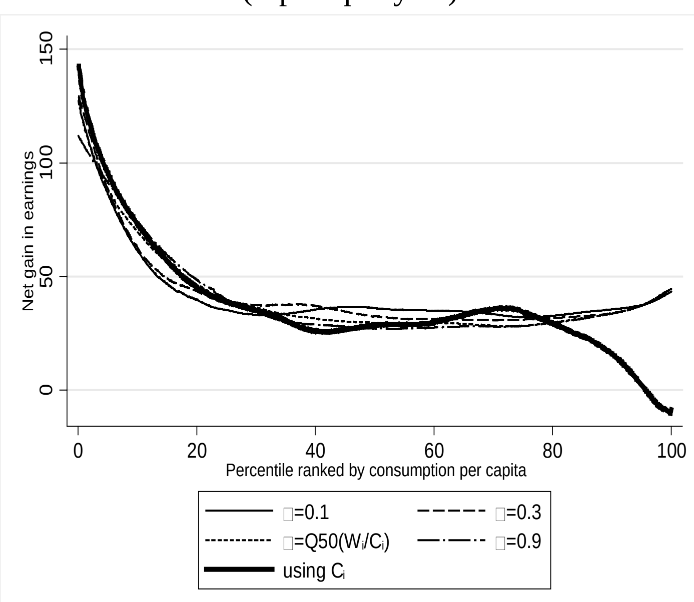


(share of post-NREGS consumption)

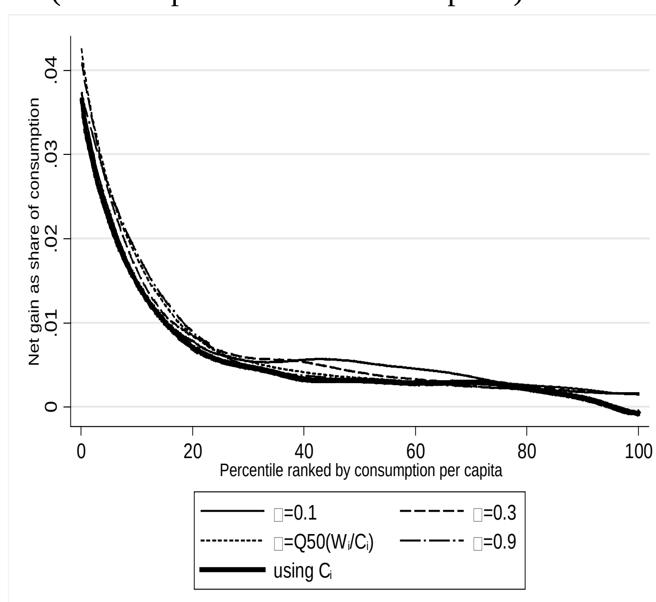


Un-rationed only

(rupees per year)



(share of post-NREGS consumption)



Note: Ranked by pre-NREGS consumption.