Size Does Matter: Migrant Experience of Urban Poverty Across Different Size Indian Cities

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Statement of the problem

By the year 2030, 590 million Indians will become urban residents, a figure twice the size of the United States population today. This means an addition of approximately 300 million to the current size of India's urban population in a short span of 20 years; a significant proportion of which will be a result of rural-urban migration. At the same time, Indian demographers have repeatedly expressed concern that urbanization process has become concentrated in larger cities (Kundu, 2011). However, preliminary reports from data released by Census 2011 not only points to increased rural-urban migration, but more significantly, a notable shift in rural-urban migration to smaller cities (Nijman (2012). With increased population pressure on rural land, shrinking share of agricultural contribution to India's GDP and an increasing share of urban contribution to the national GDP (currently close to 70%), the impetus of rural populations to move to urban areas is likely to remain strong in the coming decades. Undoubtedly, prospects of Indian cities are greatly tied to migrants' ability to transition into productive urban residents. This paper places rural-urban migrants at the center of an exploration of urban inequality in India and seeks to understand their wellbeing as urban residents. The analysis stratifies Indian cities in two categories—those with a population of one million or more, and those below one million—to answer the question: *how are migrants faring in Indian cities as compared to non-migrants, across these city size classifications?*

Data

The data for this study is obtained from the urban sample of the 64th Round (2007-08) of the National Sample Survey Organization (NSSO) data, which is the most recent national level data available with detailed migration information. The migration data from 2007-08 round were recently released and have not yet been analyzed for migrant outcomes aside from summary statistics provided in the NSS official report. The NSSO's nationally representative surveys were initiated in the year 1950 and are known to be the world's first system of household surveys applying the principles of random sampling (Deaton and Kozel, 2005). The basic design for urban areas followed is stratified two-stage sampling. Only the urban sample of the survey data is used for the purposes of this study and only individuals aged 15 and above have been included in the analyses, resulting in 144,574 individuals in the all-India sample (see Table 1 for sample characteristics).

The survey contains questions on individuals' migration history, including duration of stay in the destination, and other key socio-demographic characteristics such as age, gender, caste, religion, marital status, education etc. The paper uses non-parametric methods to describe the patterns of poverty across migrant and non-migrant populations using the detailed consumption-expenditure data collected in the survey. The consumption-expenditure data is collected across two categories, food items in last 30 days (6 items) and non-food items in last 30 days (4 items).

Migrant is defined as someone who has, at any time in the past, established a residence in a place outside the boundaries of the urban center where he/she is enumerated, for at least six months. The migrant population is divided into rural-urban migrants and urban-urban migrants for the analysis. This allows us to engage with the question of whether the two types of migrants and non-migrants face deprivations along the same dimensions of wellbeing in the urban destination or not. The paper then moves on to multivariate regression models to provide some insight into the socio-demographic characteristics of individuals that are positively or negatively associated with measures of migrant wellbeing.

Methods

Dependent variable

In order to determine wellbeing, I take advantage of the Multidimensional Poverty Index (MPI) based on the Alkire-Foster method (Alkire and Foster 2011) using the Food and Non-Food consumption-expenditure items. The Alkire-Foster methodology (AF method, hereon) identifies the poor population using a "dual cutoff" method. First, a cutoff is applied to each dimension below which a person is considered deprived. In this paper, each of the 10 consumption-expenditure items are applied the first cutoff at the bottom quintile to identify those deprived in each dimensions (i.e. each consumption expenditure item). Since cost of living and consumption patterns differ significantly in large cities as compared to smaller cities, the cut-offs were determined separately for the two groups of cities. Following this, a second cutoff is applied to specify the breadth of deprivation i.e. on how many dimensions should a person be deprived to be considered poor or not well off. This allows us to specify an identification function that assigns a value of 1 if a person is poor, or 0 otherwise. Alkire and Foster (2011) suggest beginning with a breadth of two dimensions and moving up from there. In the full paper, I explore poverty in *two and three dimensions respectively*. This procedure also allows for the specification of weights for each of the dimensions. However, given the lack of an available theory to decide the relative importance of consumption dimensions, I assign equal weights for all the dimensions in the analysis.

The reason for carrying out this analysis is twofold. One, it allows us to understand the level and distribution of wellbeing across the three subgroups. This is derived by first calculating each dimension's censored headcount ratio i.e. percentage of the overall population of a subgroup who are both poor and deprived in the given dimension and then calculating the weighted average of the dimensional headcounts within a subgroup to get the *adjusted headcount ratio* (M_0), which provide us with a sense of overall poverty across sub populations. Two, and more importantly, it allows us to answer the question whether *migrants and non-migrants face deprivations along the same dimensions of poverty?* In other words, I decompose the constituent dimensions that contribute to the overall lack of wellbeing for each of the three populations in order to better understand (a) the nature of urban poverty and (b) the uniformity or non-uniformity of its constituent components across these sub populations.

I begin by decomposing household consumption to understand the contribution of each of its dimensions to overall poverty for each of the three subgroups of the sample population, namely, non-migrants (native urban residents), rural-urban migrants and urban-urban migrants. As mentioned before, the household consumption for the last 30 days can be divided into:

- Food items in household consumption expenditure in last 30 days including consumption of cereal (and cereal products); pulses (including beans etc.); dairy and dairy products; oil; fruits and vegetables; sugar/honey; spices, condiments and processed food (6 items)
- Non-food items in household consumption expenditure in last 30 day that can be divided into: cooking fuel and electricity; entertainment expenses (including fees for sports, clubs, cable television etc.); personal care items; and consumer services and conveyance costs (4 items)

I further take advantage of the Multidimensional Poverty Index (MPI) to generate a binary category of Non-Poor and Poor to be used in a logistic regression model predicting the odds of being poor. This binary specification of poor and non-poor can be seen as a combined measure of poverty that includes all the individual components specified by the indices above. This method designates a person as poor or non-poor based on his/her depth and breadth of deprivations experienced. In other words, the method takes into account the level of poverty in each of the multiple dimensions specified by the researcher and then further takes into account the number of dimensions that a person is deprived in, to jointly classify a person as poor or non-poor. The population is then split into "Poor" (those experiencing N or more deprivations across all dimensions) and Non-poor. This is coded as a binary (0,1) variable where 1 describes those who are Poor. For use in the logistic regression model, I specify a person as "poor" if he/she is deprived in three or more of the 10 consumption-expenditure dimensions.

Independent variables

I specifically assess the effect of *(a) migrant status (rural-urban migrant, urban-urban migrant and non-migrant) (b) individual's age (c) household size (d) religion (e) caste (f) education (g) sex*. This analysis allows us to compare categories of migrants compare with non-migrants in terms of their wellbeing in urban destinations after controlling for other socio-demographic characteristics. Additionally, I also estimate the effect of *duration of stay in destination* on migrants' wellbeing. Some of descriptive characteristics of the overall sample are provided in Table 1. To highlight a few of these comparisons, we can see that the mean age of the two populations is from mid to late 30s, with migrants on an average being older than non-migrants. There are more men than women in the sample for both migrants and non-migrants. Substantially more migrants are married as compared to non-migrants, which might be due to the fact that age of marriage in rural India is lower than that in urban India. Plus, families often want a migrant son to be married before leaving in order to ensure strong ties with the rural home. In these cases, a migrant's wife often stays back in the village to live with her in-laws while the migrant finds a foothold in the city. With respect to education, more migrants as compared to non-migrants have below primary education. But at the upper end of education, '*Graduate and Above*', the percentages across two groups are essentially the same; and more migrants have completed secondary education as compared to non-migrants. As expected, there are more Hindus than Muslims but the proportions of Muslim are similar to what one would expect based on Census 2001 data. Finally, the mean monthly per capita expenditure is also similar for both groups.

Table 1: Descriptive characteristics of the urban sample for individuals aged 15 and above

Individual Characteristics	**Migrant**	**Non-Migrant**
Mean age (SD)	39.45 (SD=15.18)	34.87 (SD=16.39)
Sex		
Male	65.21 %	62.31 %
Female	34.79 %	37.69 %
Caste		
Scheduled Caste and Tribes	18.55 %	22.62 %
Other Backward Caste	33.19 %	34.15 %
Other	48.26 %	42.23 %
Religion		
Hindu	79.68 %	69.51 %
Muslim	12.13 %	18.87 %
Other	8.18 %	11.62 %
Marital Status		
Never Married	13.79 %	40.40 %
Currently Married	77.40 %	53.80 %
Widowed/Divorced/Separated	8.81 %	5.80 %
Education Category		
Below Primary	29.22 %	19.72 %
Between Primary & Secondary	27.17 %	30.91 %
Between Secondary & Graduate	27.66 %	15.95 %
Graduate and above	15.95 %	15.71 %
Mean Household Size (SD)	4.86 (SD=2.64)	5.58 (SD=2.76)
Place of Origin		
Rural	40.90 %	NA
Urban	50.10 %	NA
Monthly per capita expenditure in Rupees		
Mean in Rupees	6307.80 (SD= 4951.064)	6444.35 (SD=4846.481)
Median in Rupees	5182.5	5335

Preliminary results[1]

The results of the logistic regression model show that in Million Plus cities, rural-urban migrants are 1.8 times as likely to be classified as poor on this measurement as compared to non-migrants, holding all else constant. The result is statistically significant at a significance level of .001. In contrast, there is no significant difference in the odds of being poor between migrants and non-migrants in cities with population less than a million. In fact, urban-urban migrants are 0.75 times less likely than non-migrants to be classified as urban poor at a 0.01 level of significance. In the models presented here, 'duration' is coded as 0 for non-migrants. Migrants who arrived in the year of the survey are coded a 1 on the duration variable. The model for Million Plus cities suggest that length of stay seems to have the effect of lowering the odds of being poor as time in destination increases for migrants. However, the odds ratio is very close to 1 signaling a very small effect. In both types of cities, educational achievement has a strong and highly significant negative effect on poverty. But being from historically oppressed castes

[1] The results of the distribution of wellbeing using the AF method—decomposed across sub-groups and across constituent items of the index—are not presented as part of this extended abstract due to space constraints. These will be discussed in detail in the final paper as they highlight important differences in the nature of poverty for the three groups. Only the results of the logistic regression are presented here.

(Scheduled Tribes, Scheduled Castes and Other Backward Castes) significantly increases the odds of being poor as compared to those from the historically privileged castes; and Muslim have higher odds of being poor as compared to Hindus.

Table 2: Logistic Regression Results for Predicting the Odds of Being Poor

	Million Plus Cities			Other Cities		
	Model 3					
Individual Characteristic	**Coeff**		**Robust Std Error**	**Coeff**		**Robust Std Error**
Migrant status (Ref: Non-Migrant)						
Rural-Urban	1.81	***	*0.28*	1.02		*0.08*
Urban-Urban	1.42		*0.35*	0.75	**	*0.07*
Duration	0.98	***	*0.01*	1.00		*0.00*
Age	0.99	***	*0.00*	0.98	***	*0.00*
Education categories (Ref: Below Primary)						
Between Primary & Secondary	0.51	***	*0.05*	0.45	***	*0.02*
Between Secondary and Graduate education	0.26	***	*0.03*	0.23	***	*0.01*
Graduate and above	0.16	***	*0.02*	0.13	***	*0.01*
Caste (Ref: historically non-discriminated castes)						
Scheduled Tribes	1.52	*	*0.27*	2.10	***	*0.17*
Scheduled Caste	1.69	**	*0.33*	1.57	***	*0.11*
Other backward castes (OBC)	2.13	*	*0.71*	1.84	***	*0.27*
Religion (Ref: Hindu)						
Muslim	2.06	***	*0.38*	1.34	***	*0.10*
Other	0.72		*0.24*	0.82		*0.12*
Household Size	1.22	***	*0.04*	1.16	***	*0.02*
Sex (Ref: Male)						
Female	0.76	***	*0.04*	0.84	***	*0.02*
Observations	22609			122027		
Pseudo R-squared	0.15			0.13		
Log-Likelihood	-29166015			-77333664		

Note: *** p<0.001, ** p<0.01, * p<0.05; Reference group in parentheses; Robust Standard Errors italicized

Discussion

The analysis indicates that the scale of the city influences rural-urban migrants' experience of urban settlement. Larger cities that have served as popular migrant destinations for many decades in India are fraught with challenges of urban poverty for migrants. However, it is heartening to see that in the non-million plus cities, migrants fare much better with respect to urban poverty. This is especially pertinent given the preliminary results of Indian Census 2011 that find a shift in rural-urban migration streams to smaller cities (Nijman 2012). Explanations and implications of these results will be explored in greater detail in the final paper, especially in the context of India's economic geography and broader settlement patterns.