JOURNAL OF REGIONAL SCIENCE, VOL. 39, NO. 4, 1999, pp. 689–711

POOR AREAS, OR ONLY POOR PEOPLE?*

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ABSTRACT. Anti-poverty programs often target poor areas even when there is seemingly free migration. Should such programs focus instead on households with personal attributes that foster poverty, no matter where they live? Possibly not; there may be "hidden" constraints on mobility, or location may reveal otherwise hidden household attributes. Using survey data for Bangladesh we find significant and sizable geographic effects on living standards after controlling for a wide range of nongeographic characteristics of households, as would typically be observable to policy makers. The geographic structure of living standards is reasonably stable over time, consistent with observed migration patterns, and robust to testable sources of bias.

1. INTRODUCTION

Every country has poor areas—places where the incidence of poverty is unusually high by national standards. In a few countries there are governmental restrictions on the mobility of capital or labor, restrictions which may perpetuate poor areas. However, in most countries poor areas appear to persist without such restrictions.[1] Governments in both developed and developing countries have devised various programs to target extra resources to poor areas, with the aim of reducing poverty.

The case for targeting poor areas is not obvious in a setting in which there are no evident barriers to migration. Suppose that households are free to choose their location, that is, there exists "free migration." If the economy is in equilibrium, such that nobody wants to move, then standards of living must be completely determined by mobile nongeographic household characteristics. If geographic location were to have a welfare effect after controlling for those characteristics then households would move to the areas with positive geographic attributes. Through a spatial concentration of households with poor characteristics, an unusually high poverty rate in some area would still be

*These are the views of the authors and need not reflect those of the World Bank. The support of the Bank's Research Committee (under RPO 681-39) is gratefully acknowledged, as is the assistance of staff of the Bangladesh Bureau of Statistics, Dhaka. Helpful comments were received from Shekhar Shah, Dominique van de Walle, participants at a seminar held at the World Bank Resident Mission, Bangladesh, and the *Journal's* editors and three referees.

Received July 1998; revised October 1998; accepted December 1998.

[1]Indeed, there is evidence that migration patterns in the U.S. have reinforced the spatial concentrations of rural poverty (Nord, 1998).

Blackwell Publishers, 350 Main Street, Malden, MA 02148, USA and 108 Cowley Road, Oxford, OX4 1JF, UK.

possible in equilibrium, but, as long as it was possible to target according to nongeographic characteristics there would be no point to targeting poor areas. Any attempts to target poor areas would generate migration until a new equilibrium is restored consistent with the new distribution of nongeographic attributes. There would be no point using residential location as an indicator for targeting anti-poverty schemes.

So why target poor areas? We can suggest two main arguments. First, even without governmental restrictions on migration moving may be a costly and risky venture for poor people. Transport costs may be high. Plus there are risks at both ends; at the origin, exporting a family's temporary labor surplus may create a labor shortage later whereas at the destination there may be great uncertainties about prospects for work and housing and so on. Local personal ties of patronage or indebtedness, imperfect information, and lack of access to credit or insurance may mean that an economy is a long way from the equilibrium expected with free migration. Anthropological investigations have pointed to some of these constraints to geographic mobility in underdeveloped rural economies (for example, Das Gupta, 1987). Strong geographic effects on living standards for otherwise similar households may exist and also persist over time. This is not inconsistent with migration which could be a slow process of adjustment to geographic effects.

Second, there may also be constraints on the ability of policy makers to target household characteristics. This suggests an argument for geographic targeting in settings in which mobility is unrestricted (Ravallion, 1993). Standards of living may be completely determined by mobile nongeographic characteristics of households but a significant subset of these characteristics are unobserved by policy makers and are spatially autocorrelated due to a sorting process through migration. The key question for policy is then the quantitative importance of the geographic effects that cannot be attributed to the household attributes observable by policy makers.

What evidence can be brought to bear on these arguments? Although there is ample evidence of geographic disparities in living standards in developing countries, the disparities may be entirely accountable to spatially correlated differences in mobile nongeographic characteristics. For example, low educational attainments amongst rural people could account fully for a higher incidence of poverty in rural areas and be consistent with identical living standards for urban and rural households with the same education levels. Thus the existing evidence from geographic poverty profiles will not allow us to address the above issues.

In this paper we propose a methodology for empirically addressing these issues.[2] Our approach can be thought of as a geographic analog of the Oaxaca (1973) decomposition method. This approach has been widely used in studying wage differentials where the difference between average wages of men and

[2]For further discussion of our method of modeling living standards in this context and alternative approaches see Ravallion (1998).

women (for example) is apportioned between differences in their characteristics (including for example education, and experience) and structural differences in returns to those characteristics that arise from discrimination.[3] Analogously, we aim to determine how much of the difference in living standards between geographic areas and urban or rural sectors of a developing country can be attributed to differences in the mobile non-geographic characteristics of households versus geographic differences in the returns to those characteristics, interpretable as the underlying structural differences in living standards by location or sector.

We apply the method to Bangladesh. There are almost no administrative impediments to internal migration in Bangladesh and few physical ones because the country is spatially contiguous with over 120 million people living in an area roughly the same as that of England or Florida. Nor is it plausible that there are significant cultural or ethnic barriers to internal migration.[4] The vast majority of the Bangladeshi population share the same ethnicity, religion, and language (although there are regional dialects).

We show that sizable geographic differences in living standards in Bangladesh persist even when one takes account of the spatial concentration of households with other observable characteristics conducive to poverty. The same observationally-equivalent-household may be poor in one place but not another. Moreover, these geographic effects appear to be stable over time. Differences in nongeographic characteristics account for some of the geographic and sectoral differences in average living standards. However, our results suggest that where a person lives is independently significant, and very important quantitatively, in explaining poverty in Bangladesh.

In the next section we present the regressions and in Section 3 we discuss the implications for geographic comparisons of welfare. In Section 4 we estimate the structural profiles of average welfare and poverty and present our conclusions in Section 5. We discuss possible sources of bias in our results in the Appendix.

2. MODELING LIVING STANDARDS IN BANGLADESH

We want to see how much of the observed geographic disparities in household living standards is *structural*, meaning that it persists after controlling for nongeographic characteristics of households. The measure of standard of living we use is the log of the "welfare ratio," defined as nominal per capita consumption deflated by a date- and region-specific poverty line incorporating cost-of-living differences facing the poor in Bangladesh.[5] We assume that the welfare ratio is

[3]Recent examples are Oaxaca and Ransom (1994) and Jones and Makepeace (1996).

[4]The main exception to these observations involves the Chittagong Hill Tracks (CHT) where the country's main minority-tribal groups are found. There are also governmental restrictions on mobility into and out of CHT. We do not include CHT in our analysis.

[5]For further discussion of the theoretical properties of the welfare ratio and its advantages over other welfare indicators, including the equivalent income function, see Blackorby and Donaldson

determined linearly by a vector of household characteristics **X**, with parameters that vary geographically. Thus the mean welfare ratio will vary geographically according to (i) differences in the characteristics of households in different areas and (ii) any differences in the returns to those characteristics in different areas. To separate the two effects we estimate the mean difference in living standards conditional on some reference value $\mathbf{X}^*$ fixed across all areas. This reveals the underlying geographic structure of living standards.

We use micro data from two consecutive cross-sectional surveys for Bangladesh, three years apart. The surveys are the 1988–1989 and 1991–1992 Household Expenditure Surveys of the Bangladesh Bureau of Statistics (BBS). The surveys used virtually identical methods (in the sampling, questionnaires, and processing). They provide detailed information on the expenses of each household, including imputed values at local market prices for in-kind consumption from own production and other sources. A few nonrecurrent expenses for ceremonial activities (marriage, death) have been left out of the consumption aggregate. After data cleaning, the two survey rounds cover 5,626 and 5,725 households. Two variables can be used to define the location of households. We know if the households live in urban or rural areas, and we know to which of 17 districts each belongs.[6] The combination yields 34 "areas" in total 17 of which are rural and 17 urban.

The poverty lines are based on a food bundle widely used in poverty measures for Bangladesh. We use the survey data to estimate for each year and each area the price of each item in the food bundle, controlling for household characteristics in order to capture the price paid by the poor. The prices (unit values) from the survey were purged of differences attributed to heterogeneity in product quality (Wodon, 1997). Given that prices for nonfood goods are not available, for each year and each area we estimate an allowance for nonfood consumption. This was given by the expected nonfood spending of households whose total expenditure (food plus nonfood) equaled the cost of the food bundle; this can be interpreted as a lower bound to the nonfood allowance in a poverty line (Ravallion, 1994, Appendix 1). Summing up the allowances for food and nonfood consumption yields the total poverty lines by year and by area. We computed 14 area-specific poverty lines for each of the two survey years.[7]

(1987). Normalizing consumption by the poverty line is formally equivalent to deflating by a conventional cost of living index. We use the terms "welfare ratio" and "real consumption" interchangeably.

[6]There are 20 "Greater Districts." We dropped the CHT (see note 1), though we had no choice because there are no sample points for CHT. Two additional districts (Jamalpur and Patuakhali) have no observations corresponding to urban households. These two districts were aggregated with contiguous districts of a similar level of development. Thus we have in total 17 greater districts.

[7]Details can be found in Wodon (1997). Due to small sample sizes and to the estimation requirements we had to aggregate the 34 areas into 14 greater areas to compute the poverty lines for each of the two survey year. The computation of poverty lines for these 14 areas appears to be the best that can be done with the available data to control for price differences.

The sample sizes are not large enough to allow all parameters to vary geographically because we end up with too few observations for many combinations of district with household characteristics. Thus we estimate separate regressions for the urban and rural sectors rather than for each area using the two sets of household sample data. However, the intercept is allowed to vary by district. Other parameters are assumed to be constant within each of the urban and rural sectors, but different between them.

Let C denote the welfare ratio, given by the household's nominal consumption deflated by the date and area-specific poverty lines discussed above. We assume that $\log C$ is a linear function of a $k \times 1$ vector of nongeographic variables ($\mathbf{X}$) and an $m \times 1$ vector of locational dummy variables $\mathbf{D}$. The function differs between urban and rural samples, (denoted U and R respectively)

(1) $$\log C_i = \alpha_{\mathbf{U}} + \beta_{\mathbf{U}}'\mathbf{X}_i + \delta_{\mathbf{U}}'\mathbf{D}_i + \varepsilon_{Ui}\ (i \in U)$$

(2) $$\log C_i = \alpha_{\mathrm{R}} + \beta_{\mathbf{R}}'\mathbf{X}_i + \delta_{\mathbf{R}}'\mathbf{D}_i + \varepsilon_{\mathrm{Ri}}\ (i \in R)$$

where $\alpha_{\mathrm{U,R}}$, $\beta_{\mathbf{U,R}}$ and $\delta_{\mathbf{U,R}}$ are 1×1, $k \times 1$, and $m \times 1$ vectors of parameters and the error terms ($\varepsilon_{U,R}$) are each independently distributed with zero mean. The vector $\mathbf{X}_i$ includes

(1) Demographics: numbers of babies, children, and adults (plus their squared values); household structure (head with a spouse, head without a spouse and married, etc.,); sex of the head of household; age of the household head and its square; religion of the household (Muslim or nonMuslim). The welfare interpretation of the effect of the demographics is unclear. For example, the effect of household size could reflect an error in measuring welfare, in that scale economies in consumption within households have been ignored (Lanjouw and Ravallion, 1995).

(2) Education: the education level along four categories of the household head and spouse. To allow for possible gains from higher education among other members of the family we also include the difference between the highest education level in the household and the maximum of the education level of the head and the spouse (or of the head only when there is no spouse).

(3) Land owned: the household's land owned in four categories depending on size.

(4) Occupation: the household head's main occupation (twelve occupational classifications were used: five agricultural, six nonagricultural, and one for non-working heads).

Although this is a reasonably comprehensive list of the variables one would expect to matter to levels of living, we cannot rule out the possibility of omitted household characteristics. To the extent that these are uncorrelated with place of residence they will not bias our estimates of the geographic effects. With panel data (observing the same households over time) and suitable econometric methods one can relax this assumption and deal with geographically-correlated latent heterogeneity (Ravallion, 1998; Jalan and Ravallion, 1998).

In specifying the dummy variables, the reference household is a childless Muslim couple, both illiterate and landless, doing agricultural labor in Dhaka District. The regression coefficients should be interpreted as consumption gains relative to this reference. A table of means and standard deviations for all variables is available from the authors on request. We used the Dhaka district as the reference simply because it is the home of the capital city, though none of our simulations in section 4 would be affected by the choice of another reference district.

Our estimates of the regressions (1) and (2) are in Table 1, with White standard errors corrected for any general type of heteroscedasticity as well as for geographic clustering effects whereby the error terms for households living in the same district are allowed to be correlated.[8]

The following observations can be made:

F-tests reject the null hypothesis that coefficients are the same in urban and rural areas at the one percent level for both years for most categories of variables (Table 2).[9]

There are a number of significant demographic effects in both sectors. Chief among them is household size, the larger the household the lower its welfare ratio.

There are significant gains from education. This holds in both urban and rural areas, though the proportionate consumption gains from extra schooling are higher in urban areas.

More land yields significantly higher consumption in both urban and rural areas.

There are significant differences associated with occupation; all occupation groups are at least as well off as landless agricultural workers.

Significant geographic effects are indicated in both years (Table 1). Controlling for the above household characteristics, there are significant differences in consumption between districts and also between the rural and urban areas of given districts.

In the Appendix we present tests of how sensitive the regressions in Table 1 are to the assumptions. We test for robustness to the specification of the set of household characteristics and test for possible sample-selection bias due to rural-urban migration.

3. IMPLICATIONS FOR UNDERSTANDING GEOGRAPHIC DISPARITIES IN LEVELS OF LIVING

There are three types of geographic comparisons that we want to examine more closely: (1) the difference in mean welfare ratios between urban and rural

[8]This can be readily done using the "cluster" option in the regression command in STATA 5.0.

[9]Allowing for the geographic clustering of the data means that we can test n-1 only linear parameter restrictions where n is the number of clusters. Consequently there are not enough degrees of freedom to test whether the models as a whole differ between urban and rural areas.

TABLE 1. Regressions for Log Welfare Ratios in Bangladesh

Dependent Variable = Per Capita Consumption Expenditure Normalized by Region Specific Poverty Line	1988–1989				1991–1992			
	Urban		Rural		Urban		Rural	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Constant	0.43*	0.20	0.17	0.10	0.33	0.16	0.19*	0.07
District								
Mymensingh	–0.26*	0.01	–0.12*	0.01	–0.20*	0.01	–0.21*	0.01
Faridpur	–0.34*	0.01	–0.25*	0.01	–0.36*	0.01	–0.31*	0.01
Tangail/Jamalpur	–0.63*	0.02	–0.20*	0.05	–0.56*	0.03	–0.31*	0.03
Chittagong	0.01	0.01	0.01	0.01	–0.06*	0.01	0.13*	0.01
Comilla	–0.21*	0.01	–0.11*	0.01	–0.30*	0.01	–0.04*	0.01
Sylhet	0.12*	0.01	0.18*	0.01	0.04*	0.02	0.21*	0.01
Noakhali	–0.49*	0.02	–0.09*	0.01	–0.51*	0.02	–0.04*	0.01
Khulna	–0.13*	0.01	–0.09*	0.01	–0.20*	0.01	–0.17*	0.01
Jessore	–0.17*	0.01	–0.07*	0.01	–0.23*	0.01	–0.02*	0.01
Barisal/Patuakhali	–0.37*	0.01	–0.15*	0.02	–0.39*	0.01	–0.22*	0.05
Kushtia	–0.23*	0.02	–0.17*	0.01	–0.33*	0.02	–0.10*	0.01
Rajshahi	–0.17*	0.01	–0.06*	0.01	–0.28*	0.02	–0.25*	0.01
Rangpur	–0.19*	0.01	–0.13*	0.01	–0.28*	0.01	–0.32*	0.01
Pabna	–0.09*	0.01	–0.20*	0.01	–0.27*	0.01	–0.21*	0.01
Dinajpur	–0.32*	0.02	–0.21*	0.01	–0.33*	0.01	–0.16*	0.01
Bogra	–0.42*	0.03	–0.08*	0.01	–0.18*	0.02	–0.21*	0.01
Demographics								
Number of babies	–0.16*	0.03	–0.20*	0.02	–0.25*	0.03	–0.20*	0.01
Number of babies squared	0.01	0.01	0.02*	0.01	0.04*	0.01	0.03*	0.00
Number of children	–0.20*	0.01	–0.16*	0.01	–0.16*	0.01	–0.17*	0.01
Number of children squared	0.03*	0.00	0.02*	0.00	0.02*	0.01	0.02*	0.00
Number of adults	–0.15*	0.02	–0.10*	0.02	–0.10*	0.03	–0.11*	0.02
Number of adults squared	0.01*	0.00	0.01*	0.00	0.01*	0.00	0.01*	0.00
Sex of the head	–0.06	0.06	–0.02	0.05	0.00	0.05	–0.07	0.05
No spouse, married	0.35*	0.07	0.05	0.08	0.19*	0.04	0.20*	0.03
No spouse, single	0.27*	0.04	0.09*	0.04	0.04	0.05	0.11*	0.03
No spouse, divorced/ widowed	0.01	0.09	–0.03	0.03	–0.04	0.05	–0.01	0.05
Age of the head	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00
Age of the head squared	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Non Muslim	0.01	0.04	0.01	0.03	–0.04	0.04	–0.05	0.03
Education of Head								
Below class 5	0.11*	0.03	0.11*	0.02	0.15*	0.04	0.07*	0.02
Class 5	0.20*	0.02	0.22*	0.02	0.16*	0.03	0.10*	0.02
Class 6 to 9	0.39*	0.04	0.24*	0.04	0.28*	0.03	0.15*	0.03
Higher level	0.56*	0.05	0.48*	0.07	0.42*	0.05	0.22*	0.03
Education of Spouse								
Below class 5	0.03	0.02	0.04*	0.02	0.05*	0.02	0.05*	0.02
Class 5	0.16*	0.04	0.10	0.05	0.09*	0.03	0.12*	0.03
Class 6 to 9	0.32*	0.05	0.06	0.10	0.15*	0.04	0.17*	0.03
Higher level	0.42*	0.11	0.52	0.22	0.39*	0.03	0.26	0.12

Dependent Variable = Per Capita Consumption Expenditure Normalized by Region Specific Poverty Line	1988–1989				1991–1992			
	Urban		Rural		Urban		Rural	
	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error	Coefficient	Standard Error
Education Differential								
One level higher	0.13*	0.02	0.10*	0.02	0.04	0.03	0.09*	0.02
Two levels higher	0.26*	0.03	0.15*	0.03	0.12*	0.04	0.14*	0.02
Three levels higher	0.31*	0.07	0.26*	0.06	0.13*	0.05	0.17*	0.02
Four/more levels higher	0.35*	0.06	0.03	0.03	0.37*	0.07	0.12*	0.03
Land Ownership								
0.05 to 0.49 acres	0.09*	0.02	0.08*	0.02	0.08*	0.03	0.08*	0.02
0.50 to 1.49 acres	0.07*	0.02	0.12*	0.02	0.07*	0.03	0.17*	0.03
1.50 to 2.49 acres	0.15*	0.04	0.21*	0.03	0.09	0.04	0.27*	0.03
2.50 acres or more	0.20*	0.02	0.38*	0.03	0.25*	0.05	0.41*	0.04
Main Occupation								
Agricultural worker with land	0.12	0.07	0.09*	0.03	0.13	0.10	0.09*	0.02
Fisheries/forestry/ livestock worker	0.13	0.08	0.16*	0.04	0.31*	0.10	0.18*	0.07
Tenant farmer	0.12	0.08	0.17*	0.03	0.27*	0.09	0.18*	0.03
Owner farmer	0.22*	0.06	0.13*	0.03	0.33*	0.06	0.17*	0.03
Servant, day-laborer	0.14	0.06	0.08*	0.04	0.16*	0.06	0.09*	0.03
Transportation and communications	0.06	0.06	0.21*	0.04	0.25*	0.06	0.19*	0.03
Salesman, broker, middleman etc.	0.14*	0.07	0.20*	0.04	0.20*	0.08	0.19*	0.04
Factory worker, artisan	0.21*	0.05	0.20*	0.04	0.30*	0.10	0.15*	0.04
Petty trader, small businessman	0.32*	0.06	0.23*	0.03	0.36*	0.07	0.25*	0.03
Executive, official, profess., teacher	0.16*	0.05	0.19*	0.05	0.29*	0.07	0.26*	0.04
Retired person, student, non working	0.11	0.12	0.11*	0.04	0.34*	0.10	0.09*	0.05

Source: Authors' computations from HES unit level data. Standard errors corrected for heteroscedasticity and clustering (using the "cluster" option in STATA 5). Number of observations: 1856 urban and 3770 rural (1988–1989); 1908 urban and 3817 rural (1991–1992). $R^2 = 0.55$ (urban) and 0.50 (rural) for 1989/90 and 0.59 (urban) and 0.41 (rural) in 1991–1992. The * indicates significance at the 5 percent level. The excluded dummies are Dhaka district, married head with a spouse, male household head, Muslim religion, illiterate head, illiterate spouse, zero education differential between other members and the maximum educational level between the head and the spouse (or the head if he has no spouse), landless household, and landless agricultural worker. There is a minor difference in the way the education variables are defined between the years.

areas, which can be interpreted as the overall level of "dualism" in the country; (2) the geographic difference within each of the urban and rural sectors; (3) the difference between urban and rural areas within a given geographic area.

Comparing Urban and Rural Areas as a Whole

In 1991–1992, urban households had an average consumption of one and a half times their poverty line whereas the mean consumption of rural households barely surpassed the poverty line. What accounts for these differences? Taking

TABLE 2: Tests of Equality of Coefficients Between the Urban and Rural Regressions

	Number of restriction	F-value	F(N,18) test (1 percent level)
1988			
Constant	1	1.66	Not rejected
Nongeographic variables			
Household size variables	6	5.35	Rejected
Other demographics/religion	7	5.39	Rejected
Education variables	12	29.81	Rejected
Land variables	4	9.76	Rejected
Occupation variables	11	19.30	Rejected
Geographic variables	16	367.91	Rejected
1991			
Constant	1	0.82	Not rejected
Nongeographic variables			
Household size variables	6	1.91	Not rejected
Other demographics/religion	7	0.79	Not rejected
Education variables	12	19.98	Rejected
Land variables	4	5.18	Rejected
Occupation variables	11	4.18	Rejected
Geographic variables	16	1,059.24	Rejected

Source: Authors' computations from HES unit level data based on 114 variables in the unrestricted model.

Note: These tests test whether the coefficient estimates are equal between urban and rural areas, not whether the variables have explanatory power as a group in the urban and rural regressions.

expectations of Equations (1) and (2), the urban-rural differential in mean welfare ratios is

$$\begin{aligned}(3)\quad & \mathrm{E}\left[\log C_i \middle| i \in U, \mathbf{X}_i = \mathbf{X_U}\right] - \mathrm{E}\left[\log C_i \middle| i \in R, \mathbf{X}_i = \mathbf{X_R}\right] \\ & = (\alpha_U - \alpha_R) + (\beta_{\mathbf{U}}'\mathbf{X_U} - \beta_{\mathbf{R}}'\mathbf{X_R}) + \sum\nolimits_k (s_{Uk}\,\delta_{Uk} - s_{Rk}\,\delta_{Rk})\end{aligned}$$

where $\mathbf{X}_{\mathrm{U,R}}$ are the sample means for urban and rural areas respectively, and $s_{U,Rk}$ are the proportions of district k's population in each sector.

In Table 3 we show the components of Equation (3). The first term is the difference in the intercept, which depends on the way the other variables are defined; recall that here the intercept gives the predicted log consumption for a childless Muslim couple, both illiterate and landless, doing agricultural labor in Dhaka District. The second term represents the differential impact in urban and rural areas of nongeographic variables (again, as for any group of dummy variables, the results here are obtained relatively to the excluded dummy). Demographic differences are a minor factor in the overall urban-rural differential. For both years, about half of the differential is due to education—not only to higher education levels in urban areas, but also significantly higher returns to education. The edge provided by education in urban areas is not compensated

TABLE 3. Contributing Factors to Average Levels of Living and Urban-rural Disparities

	1988–1989		1991–1992		Urban-Rural Difference	
	Urban	Rural	Urban	Rural	1988–1989	1991–1992
Mean log welfare ratio	0.47	0.10	0.41	0.05	0.37	0.36
Decomposition						
Constant term	0.43	0.17	0.33	0.19	0.26	0.14
Geographic dummy variables	–0.11	–0.10	–0.14	–0.14	–0.01	0.00
Household characteristics	0.15	0.02	0.22	0.00	0.13	0.22
Demographics	–0.40	–0.37	–0.43	–0.40	–0.03	–0.03
Education variables	0.31	0.12	0.33	0.12	0.18	0.19
Land variables	0.06	0.15	0.05	0.15	–0.09	–0.10
Occupation variables	0.17	0.12	0.27	0.13	0.05	0.14

Source: Authors' computations from HES unit level data. Numbers may not add up due to rounding. The values in the first four columns are the contributions of the variable groups to the regressions ($\beta'\mathbf{X}$). The last two columns provide the result of the decomposition in Equation (3).

by higher land ownership and higher returns to land in rural areas. The third term is the difference due to the geographic distribution of the population, and this component is close to zero for both years. This indicates that on average and controlling for other characteristics, the gap between the urban areas of Dhaka and all the other urban areas $\left(\sum_k s_{Uk}\delta_{Uk}\right)$ is of the same order of magnitude as the gap between the rural areas of Dhaka and all the other rural areas $\left(\sum_k s_{Rk}\delta_{Rk}\right)$.

The decomposition in Equation (3) does not tell us how much of the urban-rural difference in living standards is structural because the second component reflects urban-rural differences in returns as well as characteristics. We quantify the contribution of structure below when we compare urban and rural areas within a given district.

Comparing Two Urban or Two Rural Districts

To make the second type of geographic comparison—between two urban or two rural districts at one point of time while controlling for other household characteristics—we simply compare the coefficients of the district dummies (Table 1). This is an implication of our data-imposed restriction that the slopes of other coefficients do not vary by district.

In 1991–1992, all but one of the urban and all but two of the rural district coefficient estimates are negative. Households living in the district of Dhaka appear to be better off than their urban or rural counterparts in other districts after controlling for the measured nongeographic characteristics. The comparative edge of the households in the Dhaka district makes sense because Dhaka City is the capital and it is better endowed than other areas. It is also consistent with the large migration to the capital that resulted in an annual rate of growth between 1981 and 1991 for the Standard Metropolitan Area of Dhaka of 7.3 percent, as compared to 4.1 percent for the Chittagong SMA and 4.5 percent for the Khulna SMA (the Rajshahi SMA grew at a rate of 8.0 percent). Note also that spatial effects are not limited to differences between Dhaka and the other districts. Many district coefficients are significantly different from each other.

Comparing Urban and Rural Areas Within a Given District

Making the third type of geographic comparison is slightly more complicated because the model parameters also differ between sectors. For this purpose we compute the expected gain in consumption from living in urban areas of a given district over rural areas, given that the household has the fixed reference characteristics $\mathbf{X}^*$ which we set at the national means of all characteristics. For the jth district, this is given by

$$\begin{aligned} &\mathrm{E}\left[\log C_i \middle| i \in U, \mathbf{D}_i = \mathbf{D}^j, \mathbf{X}_i = \mathbf{X}^*\right] - \mathrm{E}\left[\log C_i \middle| i \in R, \mathbf{D}_i = \mathbf{D}^j, \mathbf{X}_i = \mathbf{X}^*\right] \\ &\qquad = (\alpha_U - \alpha_R) + (\boldsymbol{\beta}_\mathbf{U}' - \boldsymbol{\beta}_\mathbf{R}')\mathbf{X}^* + (\delta_{Uj} - \delta_{Rj}) \end{aligned} \tag{4}$$

where $\mathbf{D}^j$ denotes the m-vector with 1 as the jth element and 0 otherwise. The first two terms on the right hand side of Equation (4) are the same for all districts. The first term is the same as that of Equation (3). It represents the effect of unexplained sector-wide and excluded dummy differences between urban and rural areas. The second term gives the effect of urban-rural differences in the returns to household characteristics. The term is similar to that of Equation (3) except for the fact that we conditioned on national sample means rather than on urban and rural means. When conditioning on national means we “correct” the expected consumptions obtained when conditioning on urban and rural means by adding $\beta_\mathbf{U}'(\mathbf{X}^* - \mathbf{X_U})$ to the urban consumption measures and $\beta_\mathbf{R}'(\mathbf{X}^* - \mathbf{X_R})$ to the rural measures. Urban households tend to have characteristics (fewer children, better education, better jobs) that are more favorable than the national average so conditioning on national means results in a lower estimate of their log consumption than would have been obtained with urban means. The reverse applies to rural households for which conditional log consumption using national means is higher than when using rural means.[10]

In Equation (4) the sum of the two first terms (0.21 in 1988–1989 and 0.18 in 1991–1992) accounts for the difference between the conditional consumption of households living in the urban and rural areas of the Dhaka district when conditioning on national means. For the other districts, the differences between conditional urban and rural living standards may be greater or smaller than those observed in Dhaka due to the third term $(\delta_{Uj} - \delta_{Rj})$. For 1991–1992, as can be computed from the coefficient estimates given in Table 1, $(\delta_\mathbf{Uj} - \delta_\mathbf{Rj})$ is close

[10]The terms $\beta_\mathbf{U}(\mathbf{X}^* - \mathbf{X_U})$ and $\beta_\mathbf{R}(\mathbf{X}^* - \mathbf{X_R})$ are –0.13 and 0.04, respectively, for both years. The equality for both years suggests a stability over time in the differences between each sector and the national average when the benefits of these differences are computed using the year’s returns.

to zero (i.e., it varies between –0.06 and 0.04) for half of the districts. In this first group of districts, the differences in expected log consumptions between urban and rural areas are as pronounced as those in the Dhaka district. However, for the other half of the districts ($\delta_{\mathbf{Uj}} - \delta_{\mathbf{Rj}}$) is negative and large, varying between –0.17 and –0.46, suggesting few overall differences in expected log real consumptions between urban and rural areas once we control for household characteristics and also for the sectoral geographic effects within districts. This differentiated pattern between the two groups of districts is relatively stable over time as the correlation between the sectoral geographic effects ($\delta_{\mathbf{Uj}} - \delta_{\mathbf{Rj}}$) of the two years is large and positive (0.84).

The differences in the sectoral effects ($\delta_{\mathbf{Uj}} - \delta_{\mathbf{Rj}}$) within districts are not random. The urban-rural conditional differences appear to follow divisional patterns (each administrative division consists of several contiguous districts). Most districts in the Rajshahi division (Rajshahi, Rangpur, Pabna, and Bogra) and in the Dhaka division (Dhaka, Mymensingh, and Faridpur) have large differences in standards of living between urban and rural areas after controlling for household and district characteristics (the only exceptions are Tangail/Jamalpur in the Dhaka division and Dinajpur in the Rajshahi division). In the other divisions urban and rural standards of living tend to be similar once we control for household and district characteristics. The two exceptions are the Khulna district for which urban households are better off and Noakhali for which rural households are better off. These patterns match the migration observed by the BBS (1995, 46, Table 3.5) between administrative divisions. The BBS estimated the number of lifetime net migrants for 1991 to be positive for the Dhaka and Rajshahi divisions (642,000 and 422,000 net migrants, respectively) and negative for the Barisal, Chittagong and Khulna divisions (–481,000, –285,000, and –298,000 net migrants, respectively). Thus our results are consistent with the assumption that, given their characteristics, people migrate to areas where they can obtain higher consumption.

4. SIMULATED WELFARE RATIOS AND POVERTY MEASURES

The importance of geographic structure can be assessed by comparing the actual mean consumptions and poverty measures with simulated values in which suitable controls are applied.

Simulated Welfare Ratios

Two sets of simulated welfare ratios can be computed. The first isolates the structural component by controlling for all the nongeographic characteristics; this is termed the *geographic profile of living standards*. Here we use the model to estimate for the urban and rural areas of each district the consumption of a household with the national mean characteristics ($\mathbf{X}^*$). In other words, denoting by $\mathbf{D}^j$ the geographic vector with zeroes in all rows except row j (for the jth district), we define the geographic log welfare ratio as

$$\text{(5)} \qquad \log\text{GEO}_U^i = \alpha_U + \beta_{\mathbf{U}}'\mathbf{X}^* + \delta_{\mathbf{U}}'\mathbf{D}^j$$

$$\text{(6)} \qquad \log\text{GEO}_R^i = \alpha_R + \beta_{\mathbf{R}}'\mathbf{X}^* + \delta_{\mathbf{R}}'\mathbf{D}^j$$

Equations (5) and (6) are evaluated at the same household characteristics in both urban and rural areas and across all districts so any differences are due to differences in the returns to those characteristics arising from differences in the intercept (including the geographic dummies) or slopes.

The second set of measures isolates the effects of the nongeographic characteristics by controlling for the geographic differences. We call this the *concentration profile of living standards* because it reflects the spatial concentration of nongeographic characteristics. To see how this is derived we define the concentration log welfare ratio for the urban and rural areas in district j conditional on the district's geographic characteristics as follows

$$\log\text{CON}_U^j = \alpha_N + \beta_{\mathbf{N}}'\mathbf{X}_{\mathbf{U}}^j$$

$$\log\text{CON}_R^j = \alpha_N + \beta_{\mathbf{N}}'\mathbf{X}_{\mathbf{R}}^j$$

where $\mathbf{X}_{\mathbf{U}}^j$ and $\mathbf{X}_{\mathbf{R}}^j$ represent the sample mean characteristics of the households living in urban and rural areas respectively of district j and the parameters are computed as population-weighted means

$$\alpha_N \equiv s_U\left(\alpha_U + \sum\nolimits_k s_{Uk}\delta_{Uk}\right) + s_R\left(\alpha_R + \sum\nolimits_k s_{Rk}\delta_{Rk}\right)$$

$$\beta_N \equiv s_U\beta_R + s_R\beta_R$$

in which s_U and s_R denote the urban and rural population shares and s_{Uk} and s_{Rk} are district k's share of the urban and rural populations, respectively. Doing the same for all urban and rural areas we obtain the concentration profile. By seeing how much these simulated measures vary between the 34 urban and rural areas we can assess the contribution of the concentration effects to the differences in welfare ratios.

We can ignore the residuals in the geographic and concentration conditional profiles because the residuals must sum to zero in each district due to the inclusion of dummy district variables in the regressions (if the mean residuals were not zero in a given district, a better fit could be obtained in the regression through a revised estimate for the coefficient of the corresponding dummy). Therefore, whether the residuals are due to omitted individual characteristics (in which case they should be included in the concentration profile) or to omitted area characteristics (in which case they should be included in the geographic profile), their mean vanishes in each district so that they do not affect the mean consumption level or probability of being poor of our representative households.

In Table 4 we present estimates of the actual (unconditional) and simulated sets of welfare ratios by area.[11] Consider first the geographic profile (conditioning on $\mathbf{X}^*$). Urban conditional measures of consumption tend to be larger than rural ones, in part because of the difference in constants between the urban and rural regressions ($\alpha_U - \alpha_R = 0.26$ in 1991–1992). For most urban areas the geographic log welfare ratios are lower than the unconditional ones due to the negative urban correction imposed when controlling for the mean household characteristics, set at the national mean. As noted earlier, urban households tend to have more favorable characteristics than rural households. The reverse holds for rural consumptions. Nevertheless, there is a large positive correlation between the geographic and the unconditional profiles, the correlation coefficients are 0.84, 0.81 and, 0.98 for all areas, the urban areas, and the rural areas, respectively in 1991–1992).

Consider next the concentration profile obtained using the weighted means of the urban and rural parameter estimates. Urban areas are still generally better off than rural ones, but this is because households living in urban districts tend to have nongeographic characteristics which raise living standards. The conditional (concentration) welfare measures for urban areas are again below the unconditional ones, but this time because returns to characteristics tend to be higher in urban areas than nationally, the reverse is true for rural areas. The correlation between the concentration and actual profiles is lower (0.47, 0.20, and 0.19 for all areas, urban areas, and rural areas respectively in 1991–1992) than between the geographic and actual profiles.

The spatial variance of the simulated geographic and concentration welfare ratios divided by the variance in actual values is a summary statistic that shows clearly the relative importance of geographic structure in determining living standards. Pooling urban and rural areas, the variance of the geographic profile accounts for 80 percent of that of the actual profile in 1991–1992 and the variance of the concentration profile accounts for 59 percent of the unconditional variance.

One way to check the stability of geographic effects over time is by computing the correlation between the district-level dummy coefficients of the two years. This correlation is large and positive for both the urban and the rural regressions with coefficients of 0.75 and 0.85, respectively. A more comprehensive approach taking into account not only district-level but also other types of geographic effects (sector-wide effects and sectoral effects within districts) is to compare the consumption levels of all urban and rural areas over time while holding household characteristics constant at (say) the national 1991–1992 sample means. In Table 4 we also give the conditional geographic profile for 1988–1989 using the national 1991–1992 means. As expected the correlations

[11]Notice that because the exponential operator is not linear the weighted sum of the conditional urban (or rural) log welfare ratios by district when conditioning on nongeographic characteristics need not be equal to the unconditional log welfare ratios at the mean of the urban sample as a whole.

TABLE 4: Welfare Ratios by District and by Urban/Rural Areas

Welfare Ratios (Per Capita Consumptions Normalized by Regional Poverty Lines)	Geographic Profile (given 1991–1992 National Mean Household Characteristics)				Concentration Profile (Given l991–1992 Mean Parameters)				Unconditional Profile			
	1988–1989		1991–1992		1988–1989		1991–1992		1988–1989		1991–1992	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
District												
Dhaka	1.76	1.37	1.52	1.25	1.21	1.10	1.33	1.16	1.74	1.22	1.77	1.21
Mymensingh	1.36	1.21	1.25	1.01	1.19	1.13	1.26	1.16	1.42	1.09	1.37	0.99
Faridpur	1.26	1.07	1.06	0.91	1.14	1.07	1.17	1.15	1.15	0.93	1.03	0.88
Tangail/Jamalpur	0.94	1.12	0.87	0.92	1.13	1.07	1.29	1.15	0.78	0.97	0.94	0.88
Chittagong	1.78	1.39	1.43	1.42	1.22	1.07	1.29	1.11	1.89	1.23	1.59	1.30
Comilla	1.42	1.23	1.13	1.20	1.23	1.11	1.25	1.17	1.56	1.11	1.25	1.16
Sylhet	1.99	1.64	1.58	1.54	1.12	1.06	1.08	1.15	1.79	1.40	1.47	1.49
Noakhali	1.08	1.26	0.92	1.20	1.18	1.09	1.43	1.17	1.03	1.08	1.16	1.16
Khulna	1.54	1.26	1.25	1.05	1.26	1.12	1.39	1.21	1.57	1.14	1.49	1.06
Jessore	1.49	1.28	1.21	1.22	1.23	1.11	1.34	1.16	1.48	1.13	1.37	1.19
Barisal/Patuakhali	1.21	1.18	1.03	1.01	1.29	1.14	1.41	1.19	1.21	1.08	1.23	1.00
Kushtia	1.40	1.15	1.09	1.12	1.19	1.07	1.31	1.19	1.39	0.98	1.22	1.13
Rajshahi	1.49	1.29	1.14	0.97	1.32	1.13	1.40	1.16	1.69	1.18	1.45	0.94
Rangpur	1.46	1.20	1.15	0.91	1.23	1.10	1.28	1.11	1.51	1.07	1.28	0.84
Pabna	1.61	1.12	1.16	1.01	1.17	1.02	1.30	1.08	1.61	0.93	1.31	0.91
Dinajpur	1.28	1.11	1.09	1.07	1.23	1.13	1.25	1.11	1.24	1.03	1.15	0.99
Bogra	1.16	1.27	1.26	1.01	1.02	1.08	1.07	1.17	1.48	1.11	1.12	0.99

Source: Authors' computations from HES unit level data. A value of 1 indicates that consumption is at the poverty line. The "geographic profile" controls for household characteristics (set at national mean); the "concentration profile" controls for location (by setting all parameters at national means). See text for details.

between the conditional geographic profiles for the two years are positive and large, 0.83, 0.88, and 0.83 for all areas, urban areas, and rural areas, respectively.

Poverty Measures

We can estimate probabilities of being poor from the urban and rural regressions. Assuming normally distributed errors, and conditioning on national sample means for 1991–1992, the geographic poverty profile is based on the conditional probabilities of being poor for a household living in district j[12]

$$\mathrm{Prob}\left[\log C_i < 0 \middle| i \in U, \mathbf{D}_i = \mathbf{D}^j, \mathbf{X}_i = \mathbf{X}^*\right] = \Phi\left[-\left(\alpha_U + \beta_U{}'\mathbf{X}^* + \delta_{Uj}\right)/\sigma_U\right]$$
$$\mathrm{Prob}\left[\log C_i < 0 \middle| i \in R, \mathbf{D}_i = \mathbf{D}^j, \mathbf{X}_i = \mathbf{X}^*\right] = \Phi\left[-\left(\alpha_R + \beta_R{}'\mathbf{X}^* + \delta_{Rj}\right)/\sigma_R\right]$$

for urban and rural areas respectively, where σ_U and σ_R are the standard deviations of the errors in the urban and rural regressions and Φ is the cumulative density of the standard normal.[13] For the concentration profile we condition on the weighted means of the urban and rural parameters.

Table 5 provides the unconditional, concentration, and geographic profiles for the percentage of people in each area deemed to live in households with mean consumption below the poverty line. Most urban areas have lower measures of poverty than rural areas. Note that the geographic poverty profile is based on national rather than urban means for nongeographic household characteristics. This tends to increase their poverty measures when compared to the unconditional benchmark. By contrast, the rural geographic poverty rates tend to be lower than the unconditional ones. The concentration poverty rates for urban areas are also higher than the unconditional ones because the national mean returns to characteristics tend to be lower than the urban returns. The reverse applies to the rural concentration measures. Again, the correlation between the geographic and unconditional profiles is larger than that between the concentration and unconditional profiles. In fact, the geographic poverty profile is very similar to the actual (unconditional) one. For example, the poorest area in 1991–1992 (rural Rangpur) is also the poorest when one controls for nongeographic household characteristics (65 percent are poor unconditionally; 62 percent with the controls). And the least poor area—rural Sylhet, with a poverty rate of 11 percent in 1991–1992—is also the least poor with the controls, 9 percent. When urban and rural areas are pooled, the variance of the geographic profile is equal to that of the unconditional profile whereas the variance of the concentration profile is less than half that of the unconditional profile.

[12]Note that because C_i is nominal consumption deflated by the poverty line, a negative (positive) value of its log means that the household is poor (not poor).

[13]Notice that, at the aggregate level, the unconditional and conditional measures of poverty need not be equal. Moreover, because of the nonlinearity of the normal cumulative density function we cannot provide linear decompositions of the differences between headcount indices. However, we can still compare the conditional and unconditional poverty measures obtained by district at one point of time as well as the conditional measures obtained over time.

TABLE 5: Poverty Rates by District and Urban/Rural Areas

Poverty Rate (percentage of households below the poverty line)	Geographic Profile (given 1991–1992 national mean household characteristics)				Concentration Profile (given l991–1992 mean parameters)				Unconditional Profile			
	1988–1989		1991–1992		1988–1989		1991–1992		1988–1989		1991–1992	
	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural	Urban	Rural
District												
Dhaka	6.01	18.92	12.50	24.23	44.33	54.57	34.73	48.44	15.86	33.82	13.47	39.48
Mymensingh	19.78	29.39	27.13	48.58	45.88	52.32	40.26	48.66	30.00	43.04	32.89	52.19
Faridpur	26.41	42.73	43.60	61.03	50.80	57.65	48.56	49.88	41.27	62.21	51.56	64.25
Tangail/Jamalpur	56.60	37.19	65.11	60.41	51.84	57.55	37.35	49.75	75.00	55.56	50.00	58.58
Chittagong	5.67	17.87	16.16	13.61	43.39	57.65	38.03	55.02	9.67	27.75	16.97	20.00
Comilla	16.60	28.19	36.77	28.31	42.38	53.62	40.56	48.04	26.32	38.26	37.50	34.80
Sylhet	2.96	8.29	10.46	8.85	52.94	58.78	57.09	49.57	10.71	20.60	12.50	10.78
Noakhali	41.91	26.25	59.39	28.70	47.17	56.35	27.78	47.80	25.00	51.14	37.50	37.36
Khulna	11.62	26.17	27.09	43.41	40.28	53.10	30.41	43.87	23.95	41.95	27.08	48.57
Jessore	13.57	24.48	30.10	26.37	42.72	53.75	33.91	48.71	23.44	38.22	21.88	35.79
Barisal/Patuakhali	30.01	32.41	47.29	49.23	37.32	51.33	28.68	45.73	29.03	48.76	40.63	52.49
Kushtia	17.62	34.44	40.27	35.62	46.52	57.84	36.06	45.63	26.09	57.45	34.38	38.54
Rajshahi	13.69	23.93	35.59	53.53	35.53	52.37	29.30	49.25	14.10	40.30	18.75	55.35
Rangpur	15.00	30.55	34.83	62.00	42.48	54.95	38.52	54.63	15.87	46.39	28.13	65.30
Pabna	9.63	37.28	34.18	48.22	48.22	62.91	36.77	58.19	12.50	54.69	27.91	62.50
Dinajpur	25.11	38.28	40.84	41.97	42.49	51.60	41.40	54.02	32.81	46.86	37.10	55.11
Bogra	34.50	25.16	25.99	48.42	62.62	56.71	58.14	48.21	62.50	41.13	37.50	51.75

Source: Authors' computations from HES unit level data. The "geographic profile" controls for household characteristics (set at national mean); the "concentration profile" controls for location (by setting al parameters at national means). See text for details.

5. CONCLUSIONS

After controlling for a wide range of nongeographic household characteristics we find significant and sizable geographic differences in levels of living in Bangladesh. Poor areas are not just poor because households with observable attributes that foster poverty are geographically concentrated. There are sizable structural differences in the returns to given household characteristics such as education. There are also independent spatial differences not accountable to differences in either observable household characteristics or the returns to those characteristics.

The geographic effects are not minor. Indeed, one can account well for the spatial variance in levels of living found in the data without allowing for geographic differences in household characteristics. For example, our estimated probabilities of a household with given characteristics being poor in different areas track the actual poverty rates closely.

Our results suggest that anti-poverty programs targeted to poor areas can make sense in an economy with few obvious impediments to mobility. The case for such programs rests in part on their ability to address the geographic factors in poverty which we have found to persist after controlling for observed household characteristics. These geographic factors could well be direct effects of poor (physical or human) infrastructure on the returns to private endowments. Or they could arise from spatially-correlated heterogeneity in latent household characteristics, not necessarily observable to the researcher or the policy maker. Further work is needed to determine the nature of these geographic effects, what specific forms poor-area policies should take, and whether they are cost effective relative to alternatives. Our results suggest that there is a compelling case for further work on these issues.

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APPENDIX

The regressions used in the paper include a reasonably wide range of measurable household characteristics as controls for identifying geographic effects. Nonetheless, there may be biases due to omitted household characteristics which are spatially correlated. In this appendix, we provide tests for robustness to possible sample-selection bias due to rural to urban migration, to the choice of the poverty lines, and to the specification of the set of household characteristics.

Selection Bias

The existence of rural-urban migration suggests that place of residence may not be exogenous. To test for this source of bias we estimated the following version of the standard switching model.[14] In addition to Equations (1) and (2) we have

$$I_i^* = \alpha_C + \log G_i - \gamma_c{}' W_i + \varepsilon_{Ci} \tag{A1}$$

where $I_i = 1$ if $I_i^* > 0$ and $I_i = 0$ if $I_i^* \leq 0$. Equation (A1) gives the net gain (or loss) I_i* to living in an urban area rather than a rural area. This is a function of the real per capita consumption gain ($\log G_i$), minus any cost of living in an urban area not already included in the estimates of the poverty lines and represented by $\boldsymbol{\gamma_c}'\mathbf{W}_i$. We do not observe this net gain or loss, but we do observe the decision by each household to live in an urban ($I_i = 1$) or a rural ($I_i = 0$) area. Substituting Equations (1) and (2) in to (A1) yields the reduced form equation for the switching regression

$$I_i^* = \alpha_C + (\alpha_U - \alpha_R) + (\boldsymbol{\beta_U} - \boldsymbol{\beta_R})'\mathbf{X}_i + (\boldsymbol{\delta_U} - \boldsymbol{\delta_R})'\mathbf{D}_i - \boldsymbol{\gamma_C}'\mathbf{W}_i + \varepsilon_{Ui} - \varepsilon_{Ri} + \varepsilon_{Ci} \tag{A2}$$

[14] There are a number of expositions, including Maddala (1983, Chapter 9). An early application to migration was Nakosteen and Zimmer (1980).

Let ψ_i denote the fitted values of I_i^*, and let φ and Φ be the density and cumulative density functions of the standard normal. The conditional means of the disturbances in Equations (1) and (2) are

$$E\left[\varepsilon_{Ui}\middle|I_i = 1\right] = \sigma_{Uc}\varphi_i(\psi_i)/\Phi(\psi_i)$$
$$E\left[\varepsilon_{Ri}\middle|I_i = 0\right] = \sigma_{RC}\left\{-\varphi(\psi_i)/\left[1-\Phi(\psi_i)\right]\right\}$$

where σ_{UC} and σ_{RC} are the covariances between the error terms of the two consumption equations (1) and (2) and the error term of the switching equation (A1). This yields

$$E\left[\log C_i\middle|I_i = 1\right] = \alpha_U + \beta_{\mathbf{U}}'\mathbf{X_i} + \delta_{\mathbf{U}}'\mathbf{D_i} + \sigma_{UC}\,\varphi(\psi_i)/\Phi(\psi_i)$$
$$E\left[\log C_i\middle|I_i = 0\right] = \alpha_R + \beta_{\mathbf{R}}'\mathbf{X_i} + \delta_{\mathbf{R}}'\mathbf{D_i} + \sigma_{RC}\,\varphi(\psi_i)/\left[1-\Phi(\psi_i)\right]$$

With sample selection the estimates of σ_{UC} and σ_{RC} should be statistically significant. To estimate σ_{UC} and σ_{RC}, the usual two-stage procedure involves first estimating the reduced form given by Equation (A2), and then estimating Equations (1) and (2) using the Mills' ratios computed from Equation (A2).[15]

With our set of regressors the estimates of σ_{UC} and σ_{RC} were not significant at the five percent level (using *t*-tests). There was no sign of selection bias. This also held for a number of ad hoc alternative specifications. Thus the test suggests that we can make use of parameter estimates from the urban and rural regressions without worrying about sample selection bias.

However, this test relies on a number of assumptions that highlight the difficulty of conducting the selection test. The first set of assumptions involves restrictions on the migration process and occupational choice. Including the geographic dummies in the urban and rural consumption regressions and using the above specification for the switching equation implicitly restricts migration from rural to urban areas to take place within the same district. This is because in the switching equation, the net gain from living in urban or rural areas is district-specific for any given household due to the inclusion of the term $(\delta_{\mathbf{U}} - \delta_{\mathbf{R}})'\mathbf{D}_i$. The gain to moving from one district to another cannot be factored in. If we had migration information in the data we could solve the problem by assigning to a household leaving a rural area of district j for an urban area of

[15]If we were interested in the structural equation (A1), we could use the predicted values from Equations (1) and (2). To do so we should have variables in W not included in X and D. Although this identification condition may seem innocuous it is not straightforward to find variables that affect the location decision of households but not their real per capita consumption. In the literature on switching models, identification has often been obtained by excluding one or several variables from the consumption regressions or by using different expressions of similar variables in different equations (such as years of schooling in one case and degree obtained in the other). For us, because we do not find strong evidence of sample selection and because of the difficulties to be discussed below, we need not estimate the structural equation, so that the solution to the identification problem is of less concern.

district k the corresponding gain $\delta_{\mathbf{Uk}} - \delta_{\mathbf{Rj}}$. In the absence of migration information we are left with the choice between implicitly restricting migration to take place within districts or not taking into account sectoral effects within districts in the switching equation. The first alternative is not supported by the facts. Using the 1991 census, BBS (1995, 46, Table 3.5) found large migration between districts and larger administrative divisions.[16] The second alternative is not supported by the facts either, because geographic effects appear to be significant and consistent with observed migration (as discussed further below, areas with favorable geographic effects such as the urban areas of the Dhaka district are also those with large immigration). Note that similar reasoning can be applied to the occupation dummies. The presence of the occupation terms in $(\beta_{\mathbf{U}} - \beta_{\mathbf{R}})'\mathbf{X}_i$ in the switching regression assumes that when households decide to live in urban versus rural areas, they do not consider changing occupation. Again, this is unrealistic because most households leaving rural areas give up their agricultural jobs to take on nonagricultural jobs in urban areas. (For evidence on this point see Bowles, 1970.)

The second set of assumptions involves endogeneity problems. Some urban households may have better educated members because they live in urban areas, rather than choosing to live in urban areas because they have better educated members and the returns to education are greater there. Similarly, some households may have more land because they live in rural areas, rather than choosing to live in rural areas because they have more land and the returns to land are greater there. The potential endogeneity of household characteristics also applies to demographic variables if, for example, location affects the number of children in a household rather than the other way around. Under such endogeneity, the switching model would be misspecified.

For these reasons, our results rejecting selection bias must be deemed at best suggestive.

Measurement Error in the Poverty Lines

Welfare-measurement errors related to household characteristics will not bias our estimates of geographic effects. If, for example, the use of a "per capita" normalization does not adequately deal with economies of size in household consumption then this will be picked up by the demographic variables on the right-hand side. This alters the welfare interpretation of those variables but does not bias our estimates of the geographic effects.

However, the method of adjusting for spatial cost-of-living differences is more worrying. We may observe significant geographic effects because of

[16]Given that the Dhaka SMA is by far the largest urban area in the country and also that it has grown faster than other urban areas (except Rajshahi SMA) we could assume that the migration to the urban areas of Dhaka accounts for most of the exodus from rural areas. Then we can estimate the switching model with the choice of location being the Dhaka SMA in the first equation, and all other areas in the second. Upon doing so, we did not obtain significant estimates for the coefficients of the Mills' ratios.

measurement errors in the poverty lines used for adjusting nominal consumption to differences in costs of living between districts. Specifically, although our food poverty lines may be assumed to track differences in costs of living reasonably well, our estimates for the nonfood component of the poverty lines may be off-track since they are not based on observed differences in prices for similar goods. In defining the poverty lines used in the main text, we computed nonfood allowances equal to what the households whose *total expenditure* is equal to the cost of the food bundle are expected to spend on non-food items. In this appendix, to check the robustness of our estimates to alternative methods for defining poverty lines, we computed a second set of poverty lines entailing larger allowances for nonfood consumption. The nonfood component for an area was defined as the mean nonfood spending of households whose *food* consumption equals the food poverty line. The second set of poverty lines yields lower levels of real consumptions but in terms of district coefficients the results are not affected. The correlation between the coefficient estimates of the district dummies using the two sets of poverty lines is 0.88 for the urban regressions and 0.98 for the rural regressions. The levels of significance are virtually unaltered.

What would it take to nullify the effects of all dummy coefficients in the urban and rural regressions? As noted in Wodon (1988), because poverty lines are geographically defined and geographic dummies are included in the regressions, a different set of poverty lines has no effect on the value and significance level of the estimates of nongeographic coefficients in the urban and rural regressions. However, it has an effect on the value (but not the standard deviation) of the constant terms and the coefficients of the district dummies. Holding the urban and rural poverty lines for the Dhaka district constant, we can compute alternative poverty lines for each district yielding zero district coefficients in the two regressions. Denoting by $Z_{U,Rk}$ the original poverty lines yielding the estimates of $\delta_{U,Rk}$ reported in Table 1, the alternative poverty lines are

(A3) $$Z^*_{uk} = Z_{Uk} / \exp(-\delta_{Uk})$$

(A4) $$Z^*_{rk} = Z_{Rk} / \exp(-\delta_{Rk})$$

for urban and rural areas respectively of district k.

The implicit poverty lines computed using Equations (A3) and (A4) turn out to be implausible. The conditional consumption tends to be higher in the Dhaka district than elsewhere (whether we consider urban or rural areas) so the poverty lines in most other districts must fall to yield conditional measures of living standards similar to those existing in Dhaka. The implied differentials in poverty lines are too large to be believed. Consider urban areas; when we are using the initial poverty lines corresponding to the lower non-food allowance, the decrease in the poverty lines of the non-Dhaka districts necessary for nullifying the coefficient estimates is so large that two thirds of the districts have negative nonfood allowances if we keep the food component of the poverty lines unaltered. Even when we are using the initial poverty lines obtained with the larger nonfood allowance—corresponding to the nonfood consumption of the households spending the food poverty lines on food—the change in poverty lines needed to nullify the coefficient estimates are such that several of the districts would still need to have negative or zero nonfood allowances. The geographic effects are too large to be attributed to measurement errors in the poverty lines.

Omitted Variables

The geographic effects may also be due to omitted household variables correlated with location. The main household characteristics available in the data sets which we did not use in Equations (1) and (2) are housing attributes. These are almost certainly endogenous, though they may also be correlated with important omitted variables such as long-term wealth. We preferred to exclude housing attributes from our regressions in the main text. However, for the purposes of this test, let us suppose that the endogeneity problem is less severe than the omitted variables bias. For each household we have information on the dwelling's wall and roof material, on the number of bedrooms and their size, and on its latrine and water systems.

Adding the housing characteristics did not make much difference to the estimated parameters for the district dummies. At the five percent level, the coefficient estimates of the district dummies obtained on adding the housing variables (a total of 23 dummies) differed significantly from the estimates reported in Table 1 for only 3 of the 17 urban areas and 4 of the 17 rural areas. It remained true that we could safely reject the null hypothesis that most coefficients on either the geographic or nongeographic variables were equal in urban and rural areas.