

Migration, Sorting and Regional Inequality: Evidence from Bangladesh

Forhad Shilpi

The World Bank
Development Research Group
Sustainable Rural and Urban Development Team
May 2008



Abstract

Using household level data from Bangladesh, this paper examines the differences in the rates of return to household attributes over the entire welfare distribution. The empirical evidence uncovers substantial differences in returns between an integrated region contiguous to the country's main growth centers, and a less integrated region cut-off from those centers by major rivers. The evidence suggests that households with better observed and unobserved attributes (such as education and ability) are concentrated in the integrated region where returns

are higher. Within each region, mobility of workers seems to equalize returns at the lower half of the distribution. The natural border created by the rivers appears to hinder migration, causing returns differences between the regions to persist. To reduce regional inequality in welfare in Bangladesh, the results highlight the need for improving connectivity between the regions, and for investing in portable assets of the poor (such as human capital).

This paper—a product of the Sustainable Rural and Urban Development Team, Development Research Group—is part of a larger effort in the department to understand the implications of migration and access to market for regional inequality in living standards. Policy Research Working Papers are also posted on the Web at <http://econ.worldbank.org>. The author may be contacted at fshilpi@worldbank.org.

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

Migration, Sorting and Regional Inequality: Evidence from Bangladesh

Forhad Shilpi[†]
World Bank

JEL Classification: O18; O53; C15

Key Words: Unobserved Heterogeneity, Sorting, Migration, Quantile Decomposition

^{*} Correspondence contact: F. Shilpi, MSN MC3-300, World Bank, 1818H Street NW, Washington DC 20433, Phone: (202) 458- 7476, Fax: (202) 522 -1151, email: fshilpi@worldbank.org.

[†] The views expressed here are those of authors and should not be attributed to World Bank or its affiliates.

1 Introduction

In recent years, spatial inequality in living standards has become an important policy issue in many developing countries. Numerous empirical studies have shown that households with attributes that perpetuate poverty tend to concentrate in *poor areas* – areas characterized by poor infrastructure and amenities, and by lack of access to markets (Kanbur and Venables, 2005; Jalan and Ravallion, 2002). More importantly, rates of return to observable household attributes vary across regions even in countries with no apparent restriction on migration. In this study, we examine the differences in living standards across regions with different levels of infrastructure development focusing specifically on the differences in returns to *observed* household attributes. Instead of examining only the *mean* differences, we analyze the differences in returns over the entire distribution of real per capita household expenditure. The analysis of the spatial gaps in returns over the entire income distribution can shed light into the relative importance of different factors that may cause these gaps to persist.

Existing literature offers two broad explanations for the persistence of the spatial gaps in returns even with free factor mobility. First, in econometric estimation, return to the same household attribute can be found to differ significantly across locations if the heterogeneity across households and locations is not adequately controlled for. At least three such sources of unobserved household and locational heterogeneity can be discerned from the existing literature. According to the standard locational sorting model a la Roy (1951), households are sorted across regions in terms of both observed and unobserved characteristics. For instance, while educational attainment is observed, the ability of an individual is unobservable. The selective migration of workers with better ability to urban areas means that an individual in an urban area will earn a higher wage compared with an observationally identical individual located in a rural area. In addition to ability sorting, agglomeration economies arising from increasing returns, thick labor market externalities and knowledge spill-overs can cause wages in densely populated areas and in technologically advanced sectors to be higher (Fujita, Krugman and Venables, 1999; Overman, Rice and Venables, 2007). Moreover, if public infrastructure has a positive production externality, then workers in regions with better access

to markets and better infrastructure could enjoy higher wages relative to those located in other regions (Ravallion and Jalan, 1999; Jalan and Ravallion, 2002). The omitted variable biases resulting from the inability to control for the spatial sorting of unobserved attributes do not, however, apply to all households and all locations equally. The ability sorting and agglomeration economies may affect the wages in sectors which are technology and innovation intensive. Evidence from developing countries suggests that only a small fraction of activities in urban centers qualify for such a categorization (Fafchamps and Shilpi, 2005). Similarly, because of the predominance of agricultural activities, differences in the rates of return between rural areas across regions are likely to arise primarily from the differences in public capitals and access to markets.

The spatial differences in the rate of return to the same attribute can also be sustained in an equilibrium if migration is costly (Dahl, 2002; Kanbur and Rapoport, 2005; Bayer, Khan and Timmins, 2007). The cost of migration tends to vary across individuals and households as they face different levels of risks and costs. The migration costs are likely to be higher for the poorer and middle income households who face credit constraint as well as higher opportunity costs of disposing of existing assets. Various costs associated with migration are likely to pose no serious hindrance to the mobility of members of well-off households. Similarly, short-term migrations such as commuting and temporary migration of a member of the household involve less cost than the long-term and permanent migration of the entire household. Proximity can also influence the formation of a migration network and through it, migration flows in subsequent periods (Kanbur and Rapoport, 2005). As a result, the difference in returns to attributes will be smaller across areas which are in close proximity to each other.

Both locational sorting and migration literature thus suggests that returns to observed household attributes will vary across households depending on their position in the welfare distribution, and across regions depending on their relative proximity and locational characteristics. In this paper, returns to observed household attributes are estimated using the Machado and Mata (2005) quantile regression based decomposition technique. The estimation is carried out using household level data from two rounds of the Household Expenditure

Survey (HIES) (2000 and 2005) of Bangladesh.¹ The regional gaps in the welfare in our empirical analysis are measured by the difference in the distribution of log of real per capita consumption expenditure between regions. These regional differences in the living standards are then decomposed into a ‘sorting’ effect arising due to differences in the observed household characteristics, and a returns effect resulting from the differences in the rates of return to those characteristics.

Bangladesh provides an excellent case to study the roles of different factors in explaining the spatial differences in returns for several reasons. First, there are no administrative restrictions on migration in Bangladesh. As much of the Bangladesh’s population share the same ethnicity, religion and language, there are no serious ethnic or cultural barriers to internal migration. Despite the absence of serious barriers to labor mobility, Ravallion and Wodon (1999) has shown that both sorting and returns effects are important in explaining average regional gaps in welfare in Bangladesh.² Second, the capital city Dhaka and the main port city Chittagong have emerged as two growth centers in the country, dominating both the urbanization process and economic growth. The country is sliced into three pieces by two major Asian rivers, the Ganges and the Brahmaputra. The natural border defined by these two rivers allows us to define two regions in terms of their access to Dhaka and Chittagong without relying on potentially endogenous factors such as travel time to these centers. Specifically, we define an integrated (I) region consisting of areas which are geographically contiguous to either the Dhaka or Chittagong metropolitan areas.³ The rest of the country constitutes the less integrated (LI) region.⁴ The natural border created by the rivers hinders movement of goods and people across the I and LI regions.

¹Nguyen et al.(2007) applied this technique to separate out the contribution of covariates and that of returns to urban-rural inequality in Vietnam.

²Ravallion and Wodon (1999) used data from HIES 1988-89 and 1990-91 and carried out decomposition exercise based on the mean regressions. Our paper advances the understanding of the spatial differences in welfare in several important ways. By using the quantile regression approach, we allow household attributes to have different marginal effects depending on a household’s position in income distribution. Moreover, instead of capturing spatial effects using district dummies, we define regions in terms of differences in infrastructure endowments and natural borders. Finally, we also attempt to evaluate the contribution of different factors to the persistence of spatial difference in rates of returns.

³I region thus lies to the North of the Ganges and East of the Brahmaputra rivers.

⁴The LI region accounts for the territory that lies to the West of the Brahmaputra (Rajshahi Division) and South of the Ganges (Barisal and Khulna divisions, and a small part of Dhaka Division).

The empirical analyses uncover the presence of significant returns differences across regions and across households at a different position in the income distribution. The empirical results show that changes in the returns effect can explain much of the changes in the I-LI gap in the distribution of LRPCE between 2000 and 2005. Compared with its levels in 2000, the differences in the returns effects between the I and LI regions have become larger at the lower end (below the median) and smaller at the upper end (above the median) of the welfare distribution. The trends in the returns and covariate effects between 2000 and 2005 indicate that households at the lower end of the distribution in the LI region have become worse off not only in terms of their attributes but also in terms of the returns to those attributes. Households at the upper end of the distribution in the I region, on the other hand, have become better off in terms of their attributes but experienced a relative decline in returns to those attributes in 2005. The returns effects across rural areas in the I and LI regions are substantial for relatively well-off households who face little or no barrier to migration. This result implies that the differences in market access and public capital are indeed important in sustaining the regional gaps in welfare. Comparison of the returns effects for the I-LI gap in rural areas with that for the overall I-LI gaps points to the sorting of households with better but unobserved attributes in the I region. The downward slope of the returns effect curve for the I-LI gap in 2005 is consistent with the argument that the poorer households face an increasing cost of migration. The decomposition of the urban-rural gap in welfare within each region shows that for the lower half of the distribution, there are virtually no differences in the returns to household attributes across urban and rural areas. Within each region, rural-urban migration seems to equalize the returns to household attributes for the lower quantiles, but even for these quantiles, significant returns differences exist between the I and LI regions. The evidence thus suggests that physical barriers created by the rivers not only limit the access to markets but also impose significant migration costs on households residing in the LI region. The large returns differences observed at the upper end of the distribution in the case of the urban-rural gaps in welfare is consistent with the theoretical insights that households with better observed and unobserved attributes, and economic activities benefiting from the agglomeration economies, often cluster in urban areas.

The rest of the paper is organized as the following. Section 2 elaborates the conceptual framework. Section 3 describes the data used in the analysis. Section 4, organized in a couple of sub-sections, presents the empirical results. Section 5 concludes the paper.

2 Conceptual Framework

In order to outline the explanations for the spatial gaps in welfare distribution, we start from a simple adaptation of a locational sorting model developed in Roback (1986). Suppose V_{ij} represents the indirect utility function of a household i in location j . Following Roback (1986) and Bayer et al (2006), we specify the indirect utility function as:

$$V_{ij} = V(Y_{ij}; X_{ij}, A_j) \tag{1}$$

where Y_{ij} is the per capita expenditure by household i deflated by cost of living in location j . X_{ij} is a vector of observed and unobserved household characteristics, and A_j is a vector of amenities available in location j . If migration is free and cost-less, then in equilibrium, the following condition will hold:

$$V_{ij} = V(Y_{ij}; X_{ij}, A_j) = V_{ih} = V(Y_{ih}; X_{ih}, A_h) = c \tag{2}$$

where c is a constant. Condition in equation (2) implies that the welfare levels of households with the same characteristics will be equalized across locations. This means that a high school graduate household head, *ceteris paribus*, will earn the same level of welfare regardless of his or her location. One can still observe higher incidence of poverty in some locations, but that will be simply because of the concentration of the households with poorer attributes in those locations. In other words, the welfare differences across locations will be entirely due to the locational ‘sorting’ of households with different characteristics.

In practice, the indirect utility level enjoyed by a household is not directly observable and hence in empirical work, Y_{ij} is taken as a proxy for the welfare. With Y_{ij} indicating the welfare level, there is now a possibility that returns to high school education, *ceteris paribus*,

can be observed to vary across locations even when the equilibrium condition in equation (2) holds. To illustrate this possibility, suppose X_{ij} consists of the observed education level E_{ij} and an unobserved attribute (e.g. ability) ε_{ij} . Consider the case where two identical households live in two locations: j with better amenities (e.g. school quality) than h . If amenity is valued positively by the households, then the equilibrium condition in equation (2) implies that real wage in location j , $w(X_{ij}; A_j)$ will be lower than that in location h . The regression of Y_{ij} on household characteristics (X) will then suggest lower returns to those characteristics in the locations with better amenities particularly when the measures of some of the amenities are unobservable.

Empirical evidence from developing countries, however, suggests lower returns to the household attributes in areas with weaker infrastructure and amenities (Ravallion and Wodon, 1999; Jalan and Ravallion, 2002). Existing literature offers two possible explanations for the observed differences in returns across regions. First, even in the presence of cost-less and free migration, return to the same attribute can be found to vary significantly if the heterogeneity across households and locations is not adequately controlled for in the econometric estimation. For instance, locational sorting models a la Roy (1951) suggest that households are sorted across space in terms of observed and unobserved characteristics. Suppose, real wage in a location is a function of both observed education level (E_{ij}) and unobserved attribute (ε_{ij}). For simplicity, we assume that there is no difference in the amenity across locations and that for technological reason, activities requiring higher skill and ability are clustered in area h (e.g. urban area). From the equilibrium condition in equation (2), it follows that:

$$w(E_{ij}; \varepsilon_{ij}) = w(E_{kh}; \varepsilon_{kh}) \tag{3}$$

Since $\varepsilon_{ij} < \varepsilon_{kh}$, it follows from equation (3) that $E_{ij} > E_{kh}$. Because of the geographical sorting of skill and ability in some locations, for any given education level \bar{E} , return will be higher in location h [$w_h(\bar{E}) > w_j(\bar{E})$].

Similar to the locational sorting of unobserved attributes, firms are found to cluster in selected locations because of increasing returns to scale and better access to markets. As a result of various agglomeration economies, productivity and wages are usually higher

in locations with a higher density of population and activities (Venables, 2006). Wage in this case becomes a function not only of workers observed skills but also of the unobserved productivity enhancing effect of the clustering of activities. In equation (3), if we interpret ε to represent these unobserved externalities, then it becomes clear that the estimates of returns to observed skills (e.g. education) will be higher in locations with higher density of skilled workers and activities, and thus lower rate of poverty. Finally, when there is a positive externality from the local public goods to private production function, then firms located in areas with better public infrastructure will experience higher productivity (Jalan and Ravallion, 2002; Ravallion, 2005). Again using equation (3), it can be shown easily that even with free migration, a typical econometric estimation will provide much higher estimates of returns to factors in regions with better infrastructure and amenities.⁵ It should be noted that the resulting biases in the econometric estimation of returns will not be constant across all households and locations. Empirical evidence from developing countries shows that even in urban centers, only a small fraction of the activities use technology that can generate increasing returns or can internalize benefits from knowledge spill-overs or thick market externality (Fafchamps and Shilpi, 2005). Similarly, only a small fraction of the labor force is employed in skilled jobs. Thus sorting of unobserved household characteristics (e.g. ability) and agglomeration economies are likely to be more relevant for highly skilled workers who belong to the upper tail of the income distribution.⁶ Similarly, because of the predominance of agriculture related work in rural employment, differences between rural areas across regions are likely to be more due to the differences in infrastructure and other public goods than in agglomeration economies or ability sorting.

Second, spatial differences in the rates of return may persist when migration is costly. To see the implication of costly migration, suppose wage for a worker with a given skill is higher in location h . Let M_{ijh} be the cost of migration for worker i from location j to h . The

⁵This is because not all of the locational attributes are observable, and even when they are observable, controlling for all types of locational attributes is not feasible as one quickly runs out of degrees of freedom in regression (Elison and Gleaser, 1999). In the case of developing countries, data on the state and availability of local public goods and infrastructure are simply difficult to come by.

⁶Overman, Rice and Venables (2007) noted that the external benefits associated with thick labor markets produce clustering mainly of high skilled jobs at selected locations even in developed economies.

higher wage in h will trigger migration from j to h until a new equilibrium is reached. The equilibrium condition with costly migration becomes:

$$w(E_{ij}) = w(E_{ih}) - M_{ijh} \quad (4)$$

It follows immediately from equation (4) that wage of a worker will be lower in j compared with an identical worker in h . Evidence from developing countries suggests that cost of migration, M_{ijh} , varies across individuals and households. Migration involves risk at the origin and at the destination. Households may face a shortage of labor due to migration of its member(s) and there is a uncertainty of securing a job and accommodation at the destination. A migrant needs a relatively large amount of saving to finance his/her trip and to sustain him/her during the job search period. While the travel expenses may be of concern for the poorer households, the phase of unemployment is likely to be much shorter for them as they engage mainly in unskilled jobs. The migration cost is likely to be high for middle income households who may face longer waiting period for securing a suitable job, a disruption in household's economic activities at the origin due to labor shortage and need to dispose of their existing assets. Various costs associated with migration are likely to pose no serious hindrance to migration for well-off households.⁷ Similarly, proximity to the destination allows temporary migration as well as commuting. The costs of such short-term migrations are thus much lower than that for the long term migration of the entire household. By facilitating short-term migrations, proximity can influence the formation of a migration network and through it, migration flow in the subsequent periods reinforcing the spatial differences in returns over time (Kanbur and Rapoport, 2006).

Because of differential levels of unobserved heterogeneity and migration costs, the extent of the returns effect is likely to vary across households depending on its position in the income distribution, and across regions depending on the feasibility of short-term migration. The estimation of returns to observed household attributes requires netting out the sorting effect from the spatial gap in welfare. As a first step to separate out the sorting and returns effects

⁷In developing countries, Venables (2006) reports that higher skill workers display a significantly higher propensity to move between locations than their lower skilled counterparts.

for the entire distribution of welfare, we use the quantile regression technique to estimate the following regression for a number of quantiles:

$$Q^q(y|Z, I, U) = \beta_0^q + Z\beta_1^q + I\gamma_0^q + IZ\gamma_1^q + U\lambda_0^q + UZ\lambda_1^q + \varepsilon^q \quad (5)$$

where y is the dependent variable and $Q^q(y|Z, I, U)$ is the q th conditional quantile of y . Following Ravallion and Wodon (1999) and Nguyen et al. (2007), we take log of the real per capita household expenditure as an indicator of welfare (y). The regional gaps in welfare are measured by the differences in the distribution of the real per capita expenditure between regions. Z is the matrix of all observable household and locational characteristics other than the regional dummies. We define two regions in a country (Bangladesh in our empirical work): an integrated (I) region with better infrastructure and better access to markets, and a less integrated region (LI) which lacks easy access to markets. The regional dummy I thus takes the value of one if the location is within the integrated region and zero otherwise. There are systematic differences in the infrastructure and amenities between the rural and urban areas regardless of their location in the integrated or less integrated regions. This difference is captured by an urban dummy (U) in equation (5). The matrices IZ and UZ are matrices of the interaction of all covariates (Z) with integrated and urban dummies respectively. ε^q is the regression residual term. β_0^q is the intercept term, and β_1^q is the vector of slope coefficients for the q th quantile for the base region which is rural areas in the LI region. The vectors $\gamma_0^q, \lambda_0^q, \gamma_1^q$, and λ_1^q provide the q th quantile intercept and slope differentials associated with the integrated region and urban areas. Equation (5) is estimated for every quantile in the set $q = \{0.01, .02, \dots, 0.99\}$.

The quantile regression results are then used to carry out the Machado and Mata (2005) decomposition. Following Machado and Mata (2005) and Nguyen et al (2007), we decompose the regional welfare gaps into the part that is explained by differences in the distribution of observable household and locational characteristics (sorting effect) and the part that is explained by the difference in the distribution of returns to those characteristics (returns effect). We decompose the gap between the distribution of LRPCE in two arbitrary regions, R_i and R_j , following the step-wise estimation suggested by Machado and Mata (2005).

First, for each quantile q , we estimate the vector of quantile regression coefficients (returns), $b^i(q)$, using the data from R_i . Second, using covariates from R_j and vector of coefficients estimated for R_i , we estimate the predicted consumption expenditure as $y^p(q) = Z_j b^i(q)$ where Z_j is the matrix of covariates in R_j . For each quantile q , this generates N_j fitted values where N is the size of sample for R_j . Third, we select randomly 100 elements of $y^p(q)$ for each q and stack them into a vector y^{p*} . This y^{p*} is then used to construct the counter-factual distribution. Now the gap between the q th quantile of LPRCE of the R_i and R_j can be decomposed as:

$$y^j(q) - y^i(q) = [y^j(q) - y^{p*}(q)] + [y^{p*}(q) - y^i(q)] \quad (6)$$

Since the counter-factual distribution $F(y^{p*})$ provides the distribution of LRPCE that would have prevailed if returns to covariates in R_j had been the same as in R_i , the first term on the right hand side measures the contribution of the difference in returns to the $R_i - R_j$ gap at the q th quantile. This is known as the returns effect. The second term on the right hand side, the covariate effect, thus measures the contribution of the different values of covariates to the $R_i - R_j$ gap at the q th quantile. We generated the confidence intervals of these effects by randomly re-sampling of the R_i data at the first step of the estimation.

3 Data

The main data source for our empirical analysis is the Household Expenditure Survey (HIES) 2000 and 2005 of Bangladesh which were carried out by the Bangladesh Bureau of Statistics with assistance from the World Bank. The surveys utilized a nearly identical three-stage stratified sampling strategy to select a nationally representative sample of the households. The questionnaires for the two rounds are also nearly identical. The HIES 2000 covers 7440 households in 442 primary sampling units (psus). The sample size for the HIES 2005 is 10,080 households in 504 psus.

Each of the surveys collected a wealth of information on many aspects of the living standards including detailed household level expenditure, demographics, employment, education,

health and remittances. In addition, the detailed community level information on infrastructure and access to facilities are collected for the rural psus. We utilize these data to construct both the dependent and explanatory variables. The dependent variable of our empirical analysis is the log of real per capita household expenditure (LRPCE) measured in 2005 prices. For the purpose of poverty assessment, two separate price indices are defined. They relate to the “upper” and “lower” poverty lines.⁸ As the incidence of poverty is estimated using the upper poverty line, we used price index for the upper poverty line for deflating per capita expenditure.⁹

A critical step in the estimation of equation(5) is the identification of the integrated and less integrated regions. Perhaps because of its smaller geographical size and very high density of population, Bangladesh does not have a clearly marked “lagging” region, though the North-West region has been historically known as a region with a higher incidence of poverty. However, with the spread of irrigated agriculture, the region has become the bread basket of the country in recent years (Diop, 2005).¹⁰

In the context of Bangladesh, metropolitan cities of Dhaka and Chittagong have emerged as the main growth centers. The urbanization process as well as economic growth in Bangladesh has been dominated by these metropolitan cities - Dhaka, the capital city with a population of 10 million and Chittagong, the main port city with a population of 3.4 million. Together these two cities account for 88 percent of the population in metropolitan areas and 41 percent of the total urban population. Estimates based on HIES 2000 and 2005 indicate that the average real per capita income in these cities is about 40 percent higher than that of the other metropolitan areas. As a result of the higher living standards, Dhaka and Chittagong cities have acted as magnets for migrants experiencing more than 5 percent growth in population.¹¹ These two cities also act as the main domestic and international trading hubs and

⁸The upper and lower poverty lines differ in terms of allowances for non-food expenditure. For detail on the construction of poverty lines, please see Narayan and Yoshida (2007).

⁹The lower poverty line is used to define the incidence of extreme poverty. It should be noted that for each year, 16 area specific poverty lines are constructed.

¹⁰Despite this progress, there exists still smaller areas with very high incidence of poverty such as the marsh land.

¹¹The overall rate of population growth is about 1.5 percent according to the Population Census, 2000.

are the dominant seat of major administrative and economic functions.

Access to these urban growth centers can be used to define an integrated (I) and a less integrated (LI) region. One can use some access measures such as travel time to these cities to identify these regions. However, such measures are arguably endogenous because of the endogenous placement of road infrastructure. Instead we utilize the natural border created by two major Asian rivers, the Ganges and the Brahmaputra. These rivers sliced the country into three pieces (Figure 1). We define the I region as consisting of areas which are geographically contiguous to either Dhaka or Chittagong metropolitan area. The LI region on the other hand accounts for the territory that lies to the West of the Brahmaputra (Rajshahi Division) and South of the Ganges (Barisal and Khulna divisions, and a small portion of Dhaka division) rivers. The appendix Table A.1 shows that rural areas in the I and LI regions do not differ substantially in terms of some key infrastructure indicator (e.g. electricity coverage) except for the presence of different types of banks and distance to the capital city, Dhaka.¹² While there are differences in the urban amenities between these regions, the most important difference between the I and LI regions is that of the access to large and growing markets in major metropolitan areas. Because of a significant difference in the flow of these rivers between the monsoon and dry seasons, unreliable water transportation and a virtual lack of bridges crossing the rivers,¹³ year-round commuting for work across the LI and I is not feasible.

3.1 The Spatial Gaps in Living Standards

In order to provide a feel of the trends in our data, we start with the simple investigation of the gaps in living standards across regions during 2000 and 2005 in Bangladesh. Figure 2 displays the difference in LRPCE between the I and LI regions for all of the expenditure quantiles from 5 to 95. In 2000, the I-LI gap in LRPCE has increased with an increase in the consumption quantiles. For instance, the gap has been about 10.7 percent at the 20th percentile and 19.2 percent at the 80th percentile. This implies that rich in the integrated region has been

¹²Table A.1 is generated using the community surveys of HES 2000 and 2001. Since these surveys are conducted only in rural areas, the summary statistics in the table relate only to rural areas.

¹³The only bridge crossing the Brahmaputra, the Jamuna bridge, had started to operate in 1999.

disproportionately better off than their counterparts in the LI region compared with the extent to which poor in the I region has been better off than their counterparts in the LI region. The curve showing the I-LI gap in 2005 rotated around the 55th percentile, making the gap almost flat across all of the expenditure quantiles. Compared with 2000, the I-LI gap in 2005 has increased for all of the quantiles below the 55th percentile and decreased for all of the quantiles above the 55th percentile. For instance, the gap is about 16.4 percent at the 20th percentile and 16.2 percent at the 80th percentile. This implies that the poor (rich) in the I region has experienced a faster (slower) rate of consumption growth compared with their counterparts in the LI region.

The I region, being home to two main metropolitan areas in Bangladesh, is more urbanized than the LI region. One possibility for the observed change in the I-LI gap is that the poor in the urban areas may have gained more than proportionately in terms of consumption growth compared with the poor in the rural areas. Figure 3 illustrates the urban-rural gap in LRPCE in 2000 and 2005. As opposed to the I-LI gap, the urban-rural gap is monotonically increasing in consumption quantiles for both 2000 and 2005. More importantly, the gap has shifted downward in 2005 for all consumption quantiles.¹⁴ This means that consumption of the rural population grew at a faster rate compared with urban population in both the I and LI regions narrowing the urban-rural differences. Despite the narrowing of the urban-rural differences, the I-LI gap widened at the lower end of the LRPCE distribution.¹⁵

4 Empirical Results

For the estimation of equation (5), the vector of explanatory variables Z is constructed using the household and individual level information collected in the HIES 2000 and 2005. The demographic effects are controlled in the regression by including household size, the percentage of children (less than 13 years) among household members, the age of the household

¹⁴A detailed analysis of the urban-rural gaps within each region shows similar downward and parallel shift in the gaps in 2005 in both regions, though extent of the downward shift was more pronounced in the I region.

¹⁵Appendix Table A.2 reports the I-LI and urban-rural gaps in LRPCE from OLS and quantile regression results for a selected number of quantiles. The results confirm the overall trend observed in Figure 2 and 3. We omit discussion of the Table for the sake of brevity.

head and its squared term, and the gender of the head (female=1) as regressors. The human capital of the household is measured by four different categories of education of the member of the household with highest level of education. In addition, we included the number of male and female household members with education above primary level as separate explanatory variables. These additional education variables are introduced to capture the role of educated members of the households other than the person with highest level of education. The regressions also control for the household's non-liquid assets. This asset variable includes all types of assets such as house, land, business assets and other durable goods. We include dummies to indicate household head's main sector (agriculture, manufacturing, services) and type (private wage employment, self-employment) of employment. We included similar variables for the household head's spouse but they turn out to be statistically insignificant and are dropped from the regression. The HIES 2000 and 2005 collected community level information for the rural psus. There is, however, no information on the characteristics of the urban psus, barring us to use these variables as controls. Instead, we include dummies (U=1 or I=1) to capture any mean differences in the overall infrastructure across regions.

Appendix Table A.3 reports summary statistics for the dependent and explanatory variables for different consumption quantiles for the I and LI regions. A number of variables exhibit interesting patterns. For instance, the percentage of households receiving foreign remittances increases with an increase in per capita real consumption in both regions. Households own larger amount of assets in the I region relative to the LI region. Similarly agricultural employment is relatively less important in the I region. The percentage of household head with education above secondary level increases with an increase in LRPCE. The relationship between LRPCE and education above secondary level is however similar in both I and LI regions. Overall, the differences between the household characteristics across regions do suggest presence of some locational sorting of households. We also check the differences in household attributes across the rural and urban areas (appendix Table A.4). These differences are relatively larger compared with the I-LI region differences. This suggests a larger role of locational sorting in explaining the urban-rural differences in welfare.

4.1 Quantile Regression Results

Equation (5) is estimated using the quantile regression technique for quantiles 1, 2, ...99. The standard errors of the estimates are computed using bootstrapping technique (with 500 replications) which corrects for the bias induced by clustering and stratification used in the sample design. Appendix Table A.5 and A.6 report the detailed regression results for quantiles 5, 25, 50, 75 and 95 for 2000 and 2005 respectively.

The regression results in appendix Table A.5 and A.6 suggest that household characteristics included in the regression accounts for nearly all of the gaps between the integrated and less integrated areas in both of the survey years. Out of 99 quantile regressions, the coefficient of integrated area dummy is statistically significant at the 5 percent level in 10 regressions in 2000 and 20 regressions in 2005.¹⁶ The estimated coefficients are smaller in magnitude in 2005 compared with those of 2000 for all of the quantiles up to the 77th percentile. Only for quantiles above the 78th percentile, the coefficient of the I dummy is larger in 2005. This means that some of the I-LI gaps remain unexplained by the covariates included in the regression for the upper quantiles in 2005. In contrast, the coefficient of the urban dummy is statistically significant for a number of quantiles for the survey year 2000 but becomes insignificant for all of the quantiles in 2005.

As the covariates can explain much of the I-LI and urban-rural gaps, changes in the distribution of the covariates and that in their respective returns should be able to explain the change in the I-LI and urban-rural gaps. Some of the explanatory variables display interesting patterns across the quantiles and across the survey years. The education level of the household member with highest level of education is represented in the regression by four categorical variables: dummies indicating if household member has education up to primary level, if more than primary but up to secondary level, more than secondary but up to higher secondary degree, and finally above higher secondary level. For the survey year 2000, the coefficients of the dummies indicating up to higher secondary education are positive

¹⁶The quantiles for which the coefficient of I dummy is statistically significant are 61-63, and 70-75 in 2000, and 64-66, 79-81 and 83-96 in 2005. It should be noted that none of the coefficients are significant at 1 percent level.

and statistically significant for all of the quantiles in the our base case (rural areas in the LI region), except for the 95th percentile. For 95th percentile, only education above higher secondary level is statistically significant. The coefficient of dummy for primary education is significant only in a number of quantiles in 2000. For the survey year 2005, coefficient of primary education dummy is not statistically significant, and some of the coefficients have negative signs. Except for some of the lower quantiles, the coefficients of all other education dummies were positive and statistically significant. In both survey years, the magnitudes of the coefficients increased across the quantiles and across the education levels. For instance, for the 75th percentile in 2005, the coefficient of secondary education is 0.09, whereas it is 0.31 for up to higher secondary and 0.41 for above higher secondary education. The coefficients of interaction of education level with regional dummies indicate a large premium for above higher secondary education in the urban areas in both survey years. Apart from education, the household assets have statistically significant positive influence on its expenditure level in both survey years. The coefficient of the dummy indicating a household receiving foreign remittance is statistically significant and much larger in magnitude in 2005 compared with 2000. In both survey years, LRPCE is associated significantly negatively with the household size and the percentage of household members below 13 years of age. For the survey year 2005, several employment variables and dummy for domestic remittances have statistically significant coefficients, with expected sign.

4.2 The Returns Effect

We decompose the I-LI gaps in the distribution of LRPCE into sorting and returns effects using the Machado and Mata (2005) technique. Figures 4a and 4b display the sorting/covariate and returns effects for both survey years for quantiles 5 to 95, with 95 percent confidence bounds. In 2000, the covariate effect is negative for the lower quantiles (up to the 15th percentile) and positive for the middle quantiles (45th to 75th percentile). This implies that households up to the 15th percentile in the LI region had better attributes compared to their counterparts in the I region in 2000. The reverse is true for households belonging to the 45th to 75th quantiles. For the rest of the quantiles, there were no substantial differences in

observed household attributes across the I and LI regions. The covariate effect in 2005 has shifted upward for all of the quantiles, with upper quantiles experiencing larger magnitude of the shift. Thus, in 2005, households in the I region have better attributes than those in the LI region for the entire distribution of LRPCE except for the lowest quantiles up to the 10th percentile. Such shift in the covariate effect suggests that household level physical and human capital in the I region has experienced faster growth than that in the LI region. This could result from the selective migration of households and individuals with superior characteristics from the LI to I region. This is also possible if proximity to larger urban markets in the I region has induced faster growth particularly in physical capital. However, if the proximity to large urban centers is the main reason for the upward shift in the covariate effect, then one would expect the returns effect to shift upward as well. On the other hand, selective migration of individuals with better attributes is likely to moderate the differences in returns to those attributes between the regions.

Figure 4b depicts the returns effect along with its 95 percent confidence bounds. The returns effect is much larger than the covariate effect for all of the quantiles in 2000. While the returns effect dominates the covariate effect for the lower quantiles (up to the 50th percentile), the covariate and returns effects are of similar magnitude for the quantiles above the median in 2005. The returns effect curve has an upward slope for the higher quantiles (above the 75th percentile) in 2000. The returns effect curve has rotated in 2005, becoming downward sloping. Compared with the returns effect in 2000, the differences in returns to observed household attributes have decreased in 2005 for quantiles above the 41st percentile. The magnitude of the decrease has been larger at the higher quantiles. In contrast, the returns effects in 2005 are larger than that in 2000 for all of the quantiles below the 40th percentile. Moreover, the downward slope of the returns effect curve in 2005 implies that poorer households in the LI region not only have poorer attributes but also receive much smaller returns to those attributes compared with their counterparts in the I region. The changes in the covariate and returns effects between 2000 and 2005 for the upper quantiles are suggestive of selective migration of individuals with better attributes from the LI to I region.

While the returns effects in 2005 are smaller for the upper quantiles, they are still substantial in magnitude. For instance, for all of the quantiles above the median, the returns effects account for about half of the total I-LI gap in LRPCE, the other half explained by the covariate differences. As already noted, migration costs are unlikely to pose serious impediments to the mobility of households belonging to the upper quantiles. The presence of substantial returns differences for these households points to the importance of unobserved locational and household heterogeneity. It should be noted that activities that require better (and possibly unobserved) individual attributes, and that are subject to agglomeration economies are observed to concentrate in the urban areas. Such unobserved heterogeneity is less important in the rural areas where agriculture -an activity widely believed to be subject to constant returns to scale – remains the most important occupation. Thus, any difference in the returns effect for the relatively well-off households across rural areas in the I and LI regions are likely to be due to the differences in public capital and access to larger markets.

4.3 Market Access and Public Capital: The I-LI Gap in Rural Areas

In order to assess the role of differences in the public capitals and market access in driving returns differences across regions, we restrict our sample only to the rural areas across the I and LI regions. Figure 5 plots the returns effects for the gaps in the distribution of LRPCE between rural areas in the I and LI regions. While the patterns in Figure 5 are similar to those found in Figure 4b, the comparison of these two figures shows that for the entire range of the distribution of LRPCE in 2005, the returns effects for the I-LI gap in rural areas are smaller in magnitude relative to that for overall the I-LI gap. This points to possible sorting of households with unobserved but superior attributes in the I region. This is also indicative of the presence of possible agglomeration forces in the I region. The returns effect is particularly small in magnitude for the quantiles 91st to 95th (Figure 5). The effect is nevertheless statistically significant. Even for these quantiles, it explains more than a third of the I-LI gaps in rural areas. The presence of statistically significant difference in returns for the upper quantiles of LRPCE across rural areas suggests that overall differences in infrastructure, access to market and other productive public capitals are important in

driving a wedge in the returns to observed household attributes across the I and LI regions.

4.4 Migration Costs, Unobserved Heterogeneity and the Returns Effect

In Figure 4b, the returns effect curve is downward sloping for all of the quantiles below the 40th percentile in both survey years. This implies that differences in the returns to across the I and LI regions are much larger at the lower end of the LRPCE distribution. The returns effects curve for 2005 is steeper and lies above that for 2000 suggesting that households at the lower quantiles in the I region experienced a disproportionately large increase in returns effect in 2005. The larger returns effect for the lower LRPCE quantiles is consistent with the argument that the poor may face higher and increasing migration costs. Literature on migration suggests that costs of short-term and temporary migrations such as commuting or seasonal migration of a member of a household are lower than that of permanent migration of the entire household. Proximity to the destination makes commuting and temporary or short term migrations feasible. Such mobility of workers not only moderates the spatial differences in returns but also facilitates the formation of a migration network. Any initial advantage in the formation of a migration network is likely to lead to a greater advantage in migration in the subsequent periods given the importance of the migration network in mitigating risk associated migration. Thus households living in the close proximity of the destination are likely to face much lower costs of migration.¹⁷ If migration costs and migration networks are indeed important in regulating the flows of migrants particularly from the poorer households, then one would expect the returns effect to be smaller in areas close to the destinations. As in other developing countries, urban areas remain the most common destination of migration in Bangladesh. We estimate the returns effect for the urban-rural gaps in LRPCE distribution in the I and LI regions separately. An advantage of examining the urban-rural gap is that it can also shed light on the influence of agglomeration economies and sorting of unobserved household attributes on the returns effects across areas. This is because the sorting of households with unobserved but superior attributes and the presence

¹⁷The main costs of migration for the poor are likely to result from their inability to finance trip(s) to destination and to tap into the migration network. Proximity to destination has important bearings on both credit constraint faced by poorer households and formation of migration network.

of agglomeration economies are likely to be reflected in the returns differences for the upper LRPCE quantiles.

Figure 6 displays the returns effect in the case of urban-rural gaps in LRPCE in the I region. In stark contrast with returns effect in the case of the I-LI gap, there is practically no difference in the returns to observed households characteristics between the urban and rural areas in the I region in 2005 for all of the quantiles below the median. For these quantiles, the returns effect was slightly lower in the urban areas compared with the rural areas in 2000. For all of the quantiles above the median, the returns effect increases with an increase in LRPCE quantiles in both 2000 and 2005. The slope of the returns effect curve is much steeper in 2005 compared with that in 2000 implying that households at the upper quantiles of LRPCE distribution in the urban areas have experienced substantial increase in returns to their observed attributes. Because of such a large increase in the returns effect for the upper quantiles, the returns effect in 2005 explained more than half of the urban-rural gaps in LRPCE for them, whereas it explained about a quarter of the urban-rural gap in 2000. The large increase in the returns effect for the urban households in the upper quantiles is consistent with the evidence that main metropolitan areas have experienced higher growth of economic activities.

Figure 7 displays the trend in the returns effects for the urban-rural gaps in the LI region which is similar to that in the I region. The returns effects are insignificant for all of the quantiles below the 60th percentile in both survey years (Figure 7). While the returns effect increases with an increase in LRPCE for the upper quantiles (above the 60th percentile), its magnitudes are nearly the same for both survey years. The large returns effects for the upper end of LRPCE distribution suggest sorting of households with better but unobserved attributes in urban areas in both the I and LI regions. Such returns differences could also result from the presence of agglomeration economies in the urban areas.

The evidence in Figure 6 and 7 clearly highlights the absence of substantial returns differences between the urban and rural areas at the lower end of the distribution within each region. This implies that for the poorer households, the welfare gap between urban and rural areas has been primarily due to the sorting effect: rural poorer households have

poorer attributes relative to their urban counterparts. More importantly, migration within each region seems to equalize the returns across urban and rural areas for this part of the distribution. As the poor typically work in unskilled jobs which have little or no entry barrier, such convergence of returns across urban and rural areas within each region is expected. More importantly, the result also indicates that there is practically no serious barrier to mobility within each region for the poorer households.

Figure 8 plots the returns effect for the gaps in the distribution of LRPCE between urban areas in the I region and rural areas in the LI region. As opposed to Figure 6 and 7, the urban-rural differences in the returns are quite substantial for the lower half of the distribution in both survey years. The results show that migration across the I and LI regions involves larger costs. The mighty rivers that separate these regions do make temporary migration and commuting difficult across regions. This barrier to short term migrations combined with its implications for the formation of a migrant network seems to be responsible for sustaining and even widening the returns differences between the I and LI regions for the lower half of the distribution of LRPCE.

5 Conclusions

The spatial inequality in living standards is a fact of life in most developing countries. Empirical evidence from developing countries shows that the rates of return to observable household attributes vary across location in countries with no apparent restriction on migration. Even with free factor mobility, such spatial differences in the rates of return can be detected in the empirical work if households and activities are sorted across locations on the basis of unobserved attributes. This is also possible if regions differ in terms of local public capitals with positive externality for the private production, and/or if migration is costly. None of these factors, however, affects all of the households and all of the locations equally. The sorting of unobserved attributes is likely to be more important for households belonging to the upper tail of the welfare distribution, and residing in urban areas. For these households, migration costs are not likely to restrict their mobility. As agriculture – an activity which

is believed to be subject to constant returns to scale – predominates in the rural areas, the differences in the returns for these well-off households located in rural areas would reflect the differences in the productive public capitals as well as access to markets across regions. Migration costs affect the mobility of the households belonging to the lower to middle part of the distribution. As proximity to the destination facilitates short-term migrations and formation of the migration networks, the returns differences especially for the lower quantiles are likely to be smaller in magnitude in regions which are close by. In this paper, we examine the differences in the rates of return to observed household attributes over the entire welfare distribution and across regions with different levels of infrastructure development, market access and proximity.

The empirical evidence, based on the quantile decomposition technique pioneered by Machado and Mata (2005) and on two rounds of household level data from Bangladesh, uncovers substantial differences in the returns between an integrated (I) region contiguous to the growth poles (Dhaka and Chittagong metropolitan areas) and a less integrated (LI) region which is cut-off from the growth poles by two main Asian rivers (Ganges and Brahmaputra). The returns effect measuring differences in the rates of return to observed household attributes across rural areas in the I and LI regions is quite substantial for the upper quantiles of the welfare distribution. This result suggests an important role of the differences in public capitals and market access in sustaining the differential returns across regions. Comparison of the returns effects across different areas (rural vs overall I-LI gap) also indicates the sorting of households with unobserved but better attributes in the I region and in the urban areas within the I and LI regions respectively. The significant returns effects for the I-LI gap for the households at the lower end of distribution is consistent with the view that the poor face higher costs of migration. However, there is virtually no difference in the returns to observed household attributes across urban and rural areas within each region at the lower half of the distribution. This result along with the substantial returns effect in the case of the I-LI gaps imply that while within each region, migration seems to equalize the returns for the households belonging to the lower half of the distribution, the physical barriers created by the rivers do impose significant migration costs by hindering short-term migrations and

through it, the formation of a migration network.

The empirical results have a number of policy implications. As migration within each region moderates the differences in the returns to attributes for the poorer households, investment in enhancing the attributes of these households (e.g. human capital) can contribute significantly to reducing the gaps in the living standards. Investment in improving connectivity between the I and LI regions will not only allow better access to markets for the households in the LI region but also facilitate better flow of migrants across regions. Similarly, investment in much neglected urban services in the LI region can attract more firms and activities as well as migrants in the urban centers creating an additional engine of growth within the LI region.

References

1. Bayer, P, N. Keohane and C. Timmins, 2006, "Migration and Hedonic Valuation: The Case of Air Quality, NBER working paper #12106.
2. Bayer, P, S. Khan and C. Timmins, 2007, "Non-parametric Identification and Estimation in a Generalized Roy Model," Mimeo.
3. Dahl, Gordon B., "Mobility and the returns to Education: Testing a Roy Model with Multiple Markets," *Econometrica*, 70(6), 2367-2420, November 2002.
4. Diop, N, 2005, "Agriculture Development Strategy," in Transforming Bangladesh into a Middle Income Economy, S. Ahmed, ed., MacMillan India Ltd: Delhi.
5. Ellison, G, and E.L. Glaeser, 1999, "The Geographic Concentration of Industry: Does Natural Advantage Explain Agglomeration?" *American Economic Review Papers and Proceedings*, Vol. 89(2), pp. 311-316.
6. Fafchamps, Marcel, and Forhad Shilpi, 2005. "Cities and Specialization: Evidence from South Asia." *Economic Journal*.Vol. 115, April, 2005.
7. Fujita, Masahisa, Paul Krugman and Anthony J. Venables, 1999, *The Spatial Economy: Cities, Regions, and International Trade*, MIT Press, Cambridge and London.

8. Jalan, Jyotsna and Martin Ravallion, 2002, "Geographic Poverty Traps? A Micro Model of Consumption Growth in Rural China," *Journal of Applied Econometrics*, Vol. 17, p. 329-346.
9. Kanbur, R and H. Rapoport, 2005, "Migration Selectivity and the Evolution of Spatial Inequality," *Journal of Economic Geography*, Vol. 5(1), p. 43-57.
10. Kanbur, R and A. Venables, 2005, *Spatial Inequality and Development*, Oxford University Press: New York.
11. Machado, J.A.F. and J. Mata, 2005, "Counter-factual Decomposition of Changes in Wage Distributions using Quantile Regression," *Journal of Applied Econometrics*, Vol. 20 (4), p.445-465.
12. Narayan, A, and N. Yoshida, 2007, "Trends and Patterns of Poverty in Bangladesh in Recent Years," World Bank, *mimeo*.
13. Nguyen, B.T, J.W. Albrecht, S., B. Vroman, and M. D. Westbrook, 2007, "A Quantile Regression Decomposition of Urban-rural Inequality in Vietnam," *Journal of Development Economics*, Vol. 83, p. 466-490.
14. Overman, H.G, P. Rice and A. J. Venables, 2007, "Economic Linkages across Space," CEP Discussion Paper No. 805.
15. Ravallion, M and Q. Wodon, 1999, "Poor Areas or Poor People?" *Journal of Regional Sciences*, Vol. 39(4), p. 689-711.
16. Ravallion, Martin, 2005, "Externalities in Rural Development: Evidence for China," in Ravi Kanbur and Anthony Venables eds. *Spatial Inequality and Development*, Oxford University Press, New York.
17. Ravallion, Martin and Jyotsna Jalan, 1999, "China's Lagging Poor Areas," *American Economic Review Papers and Proceedings*, Vol. 89(2), pp. 301-305.

18. Roback, J, 1982, "Wages, Rents and Quality of Life," *Journal of Political Economy*, vol. 90, p.1257-78.
19. Roy, A. D, 1951, "Some Thoughts on the Distribution of Earnings," *Oxford Economic Papers*, vol.3, p. 135-46.
20. Venables, A, 2006, "Shifts in Economic Geography and Their Causes," *Federal Reserve Bank of Kansas City Economic Review*, Fourth Quarter.

Figure 1: Main Rivers in Bangladesh

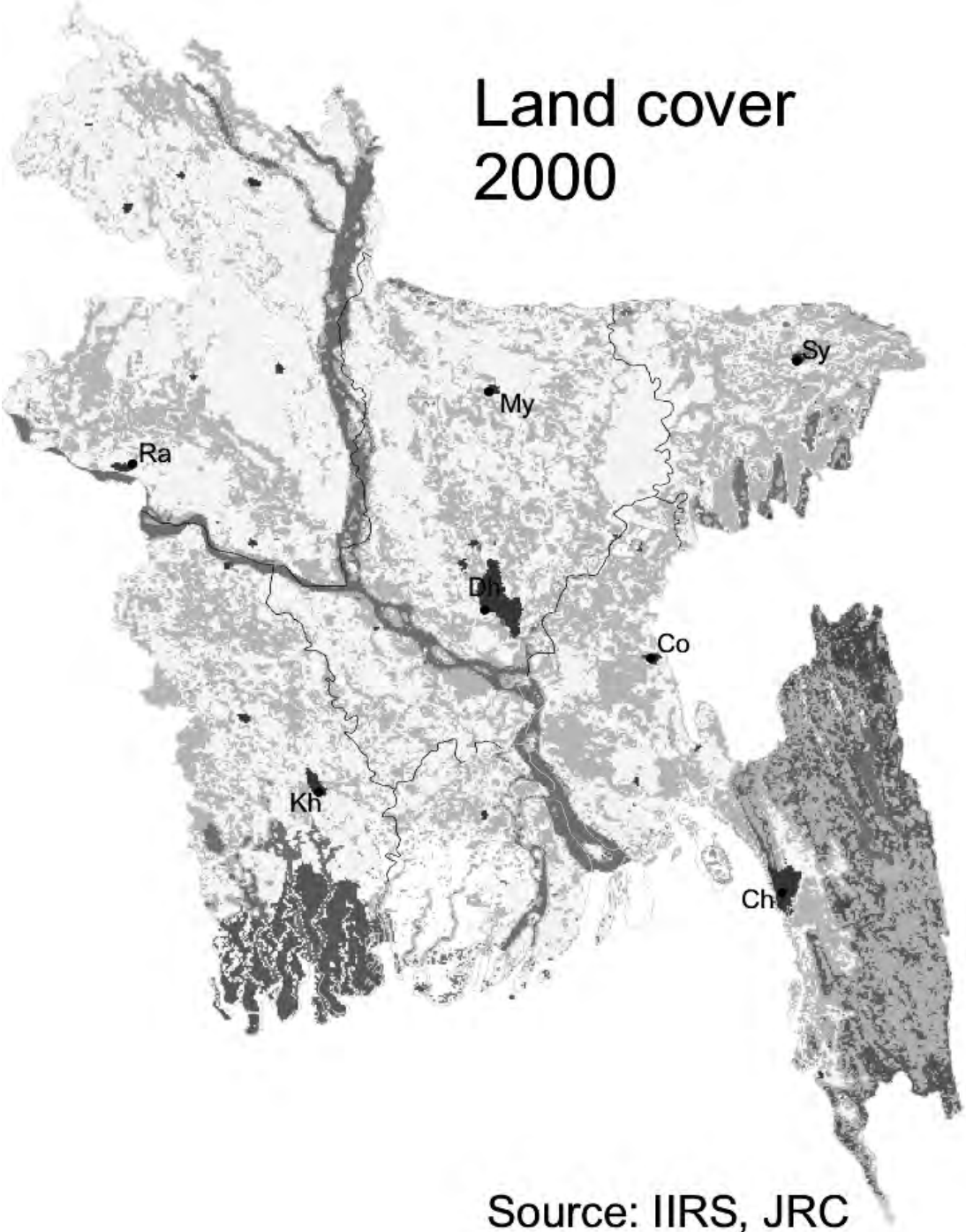


Figure 2: Integrated vs. Less Integrated Region Gap in Log Real Per Capita Expenditures

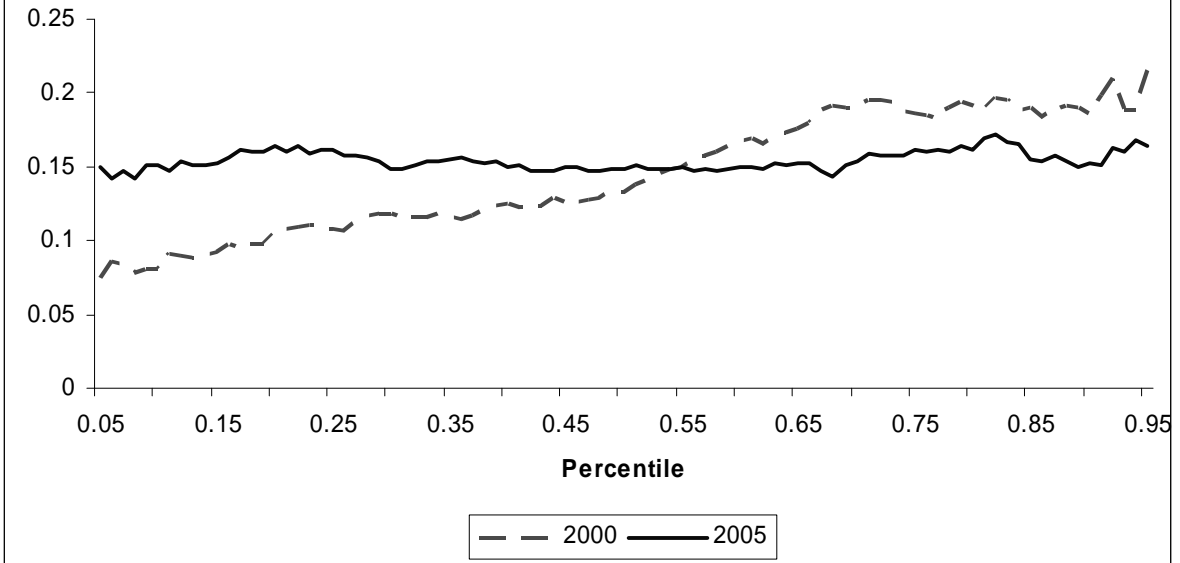


Figure 3: Urban-Rural Gaps in Log Real Per Capita Expenditures

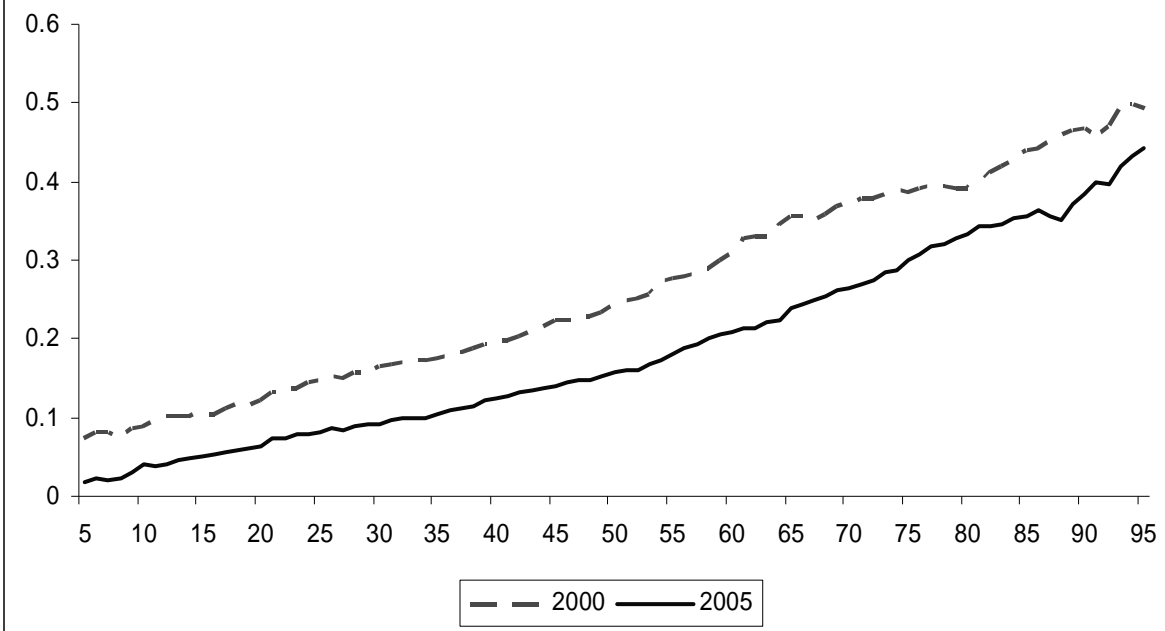


Figure 4a: Covariate Effects for I-LI Gap, 2000 and 2005
95% Confidence Interval

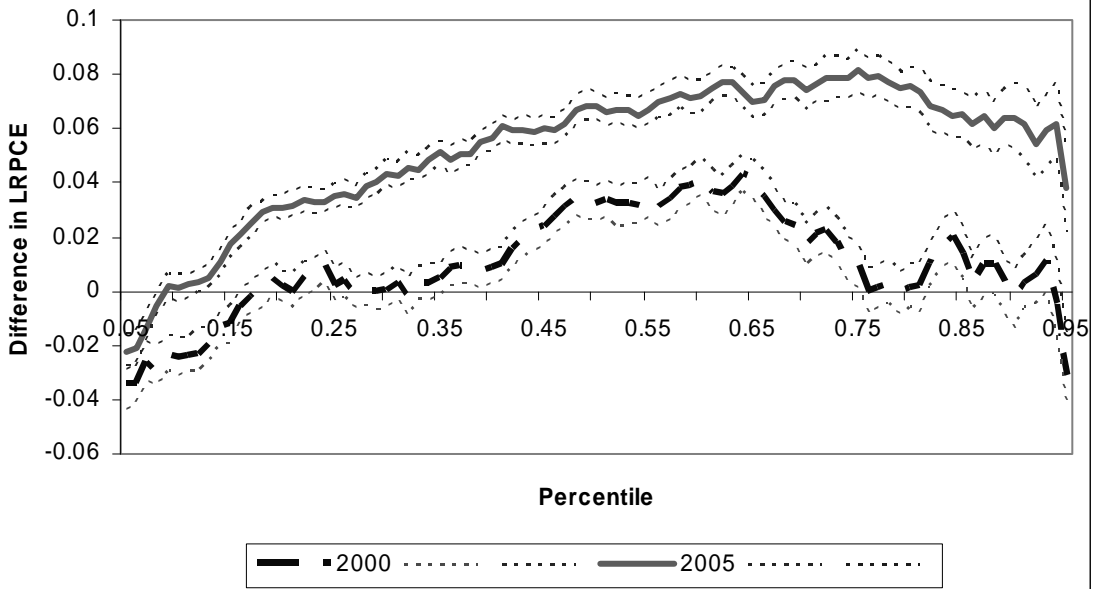


Figure 4b: Returns Effects for I-LI Gap, 2000 and 2005
95% Confidence Interval

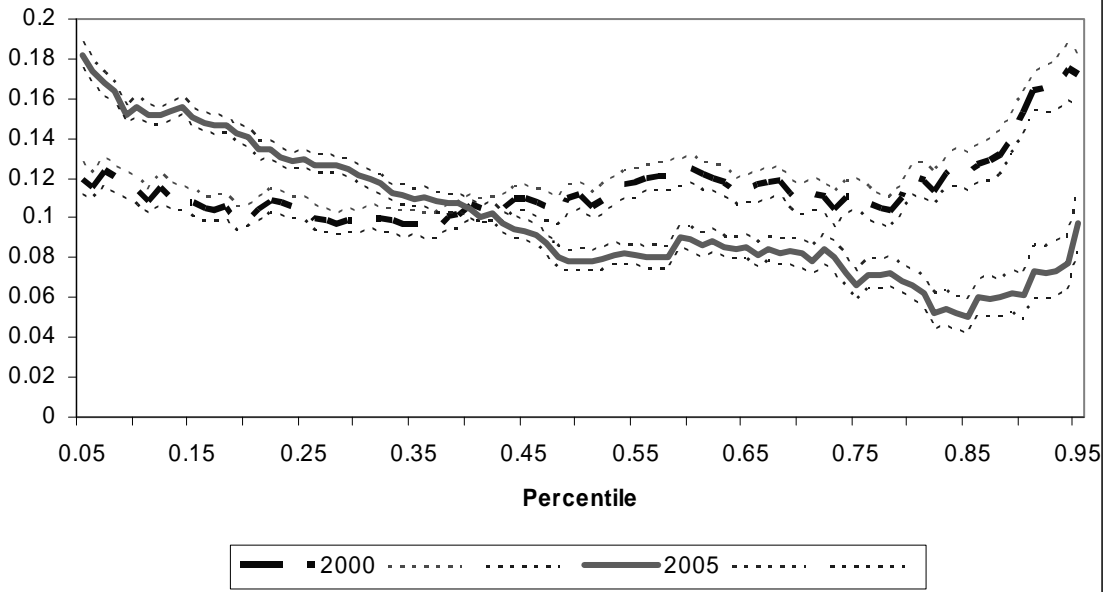


Figure 5: Returns Effects for Rural I-Rural LI Gaps, 2000 and 2005

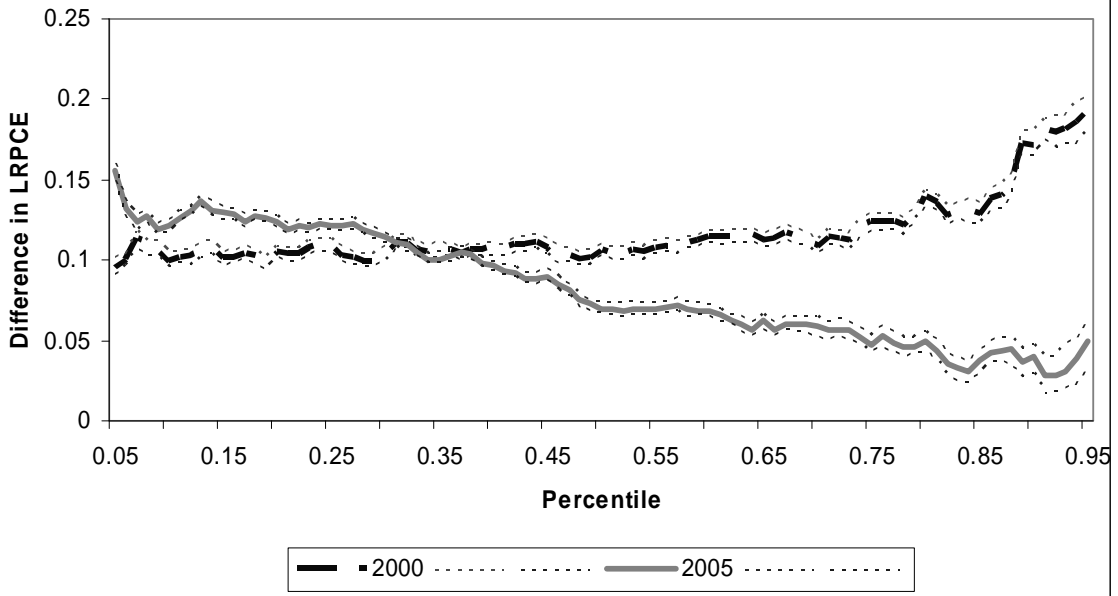


Figure 6: Returns Effects for Urban-Rural Gaps in Integrated Region, 2000 & 2005

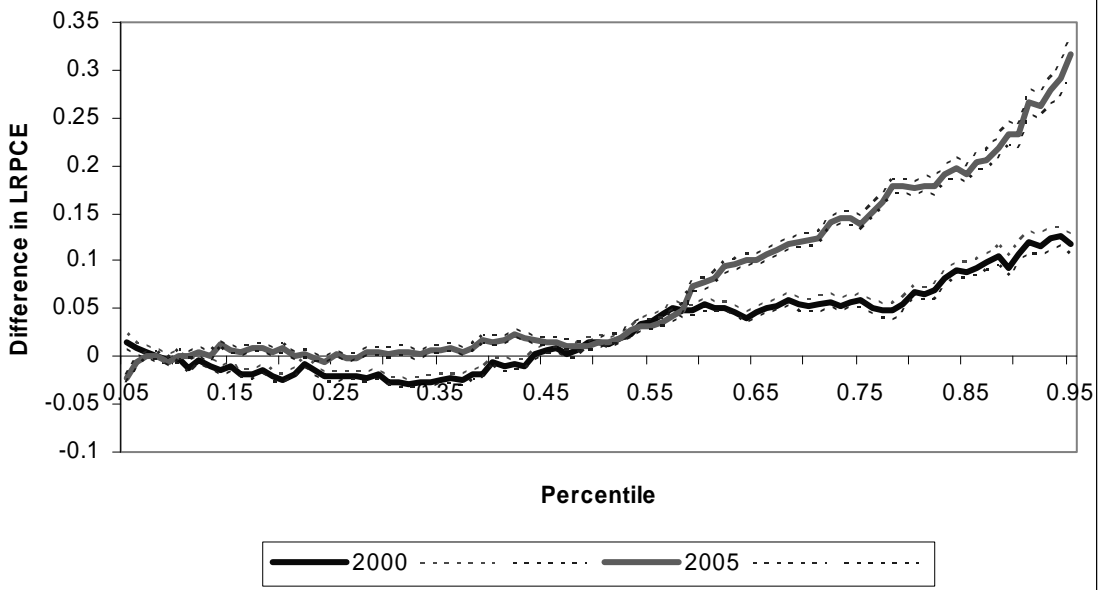


Figure 7: Returns Effects for Urban-Rural Gaps in Less Integrated Region, 2000 & 2005

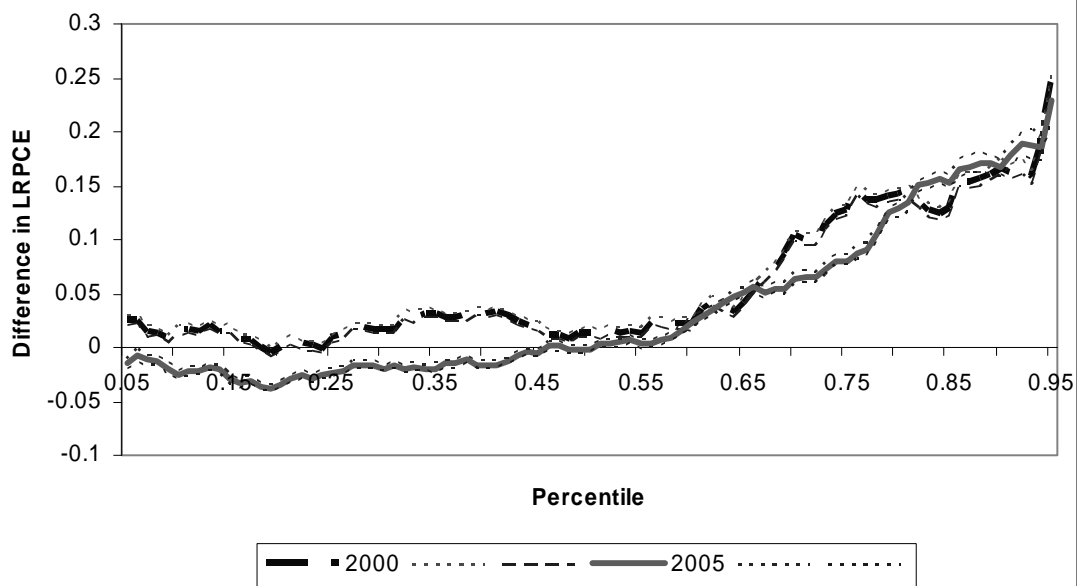


Figure 8: Returns Effects for Urban I - Rural LI Gaps, 2000 & 2005

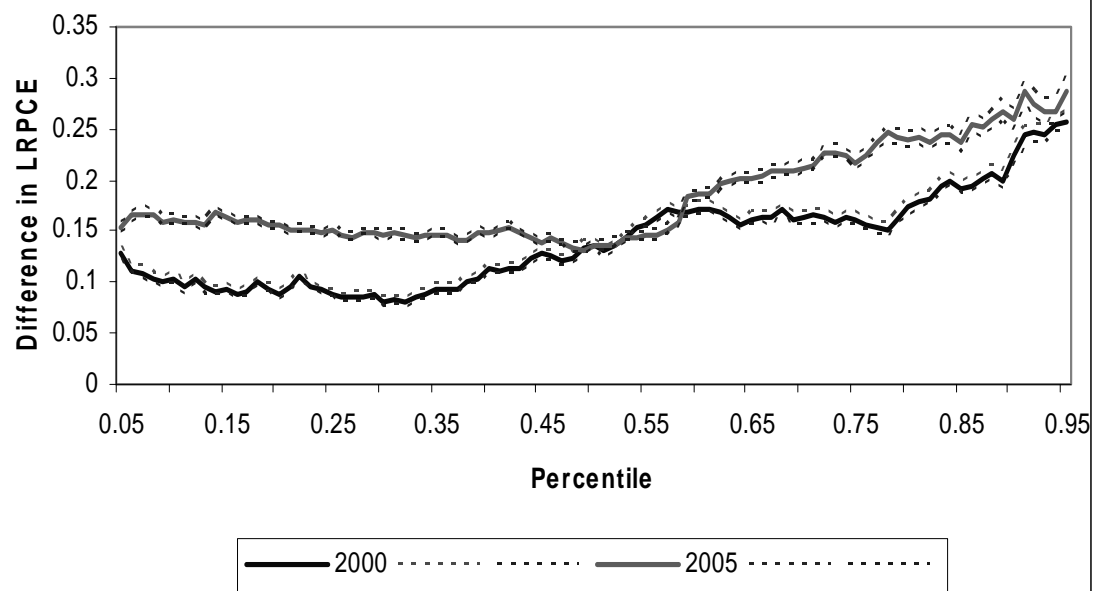


Table A.1: Indicators for Integrated (I) and Less Integrated (LI) Regions

	2001		2005	
	LI	I	LI	I
Head count Ratio (Upper poverty line)	53	46	50	33
Real per capita expenditure	727	800	1046	1207
Electricity in Mouza	67%	63%	80%	83%
BD Krishi Bank in Mouza	7%	17%	27%	45%
Commercial Bank in Mouza	17%	17%	25%	40%
Grameen Bank in Mouza	13%	13%	29%	40%
Market/bazar in Mouza	53%	61%	64%	77%
Distance to thana HQ (km)	10.7	11.1	9.7	15.5
Travel time to thana HQ ('00mins)	0.6	0.7	0.5	0.7
Distance to zila HQ (km)	27.7	33.0	28.6	33.5
Travel time to zila HQ ('00 mins)	1.1	1.2	1.0	2.0
Distance to Dhaka HQ (km)	296.2	169.7	294.4	168.7
Travel time to Dhaka HQ ('00 mins)	4.2	3.0	4.5	3.2
Any banks in Mouza	25%	24%	35%	46%

Source: HES 2000 and 2005

Table A.2 : Estimates of Regional Gaps at the mean and at different quantiles

Year	Coefficient	Mean	Quantiles				
			5th	25th	50th	75th	95th
2000	Rural-Less Integrated	6.460	5.795	6.156	6.415	6.731	7.282
	t-value	705.3	232.2	362.3	351.9	291.4	172.4
	Urban	0.25	0.08	0.13	0.24	0.37	0.51
	t-value	19.68	2.32	4.12	6.25	8.84	7.31
	Integrated	0.12	0.07	0.10	0.13	0.13	0.15
	t-value	10.19	0.19	3.88	4.54	3.46	2.66
2005	Rural-Less Integrated	6.831	6.163	6.511	6.775	7.096	7.681
	t-value	853.8	384.5	461.3	489.4	389.8	251.5
	Urban	0.177	0.007	0.069	0.145	0.280	0.436
	t-value	16.424	0.303	3.124	5.761	7.183	7.860
	Integrated	0.143	0.153	0.154	0.132	0.138	0.131
	t-value	13.487	7.648	7.228	6.060	4.733	2.527

Table A.3a: Definition of Variables

Acronym	Definition
RPC	Per capita consumption expenditure deflated by regional price index
LRPC	Log per capita consumption expenditure deflated by regional price index
I	Dummy for integrated region
U	Dummy for urban area
drs	Dummy =1 if Household Received domestic remittances
frs	Dummy =1 if Household Received Remittances from abroad
lasset	Log(Total Asset deflated by regional price index)
hsize	Household size
hhage	Household head's age
hhages	Household head's age squared
hhfem	Household head Female
hhmar	Household head Married
hedu2	HH Head has primary education
hedu3	HH Head has Secondary education
hedu4	HH Head has higher Secondary education
hedu5	HH Head has more than higher Secondary education
pchi	Percentage of children
agri	agri=1 if HH head employed in agriculture
manu	manu=1 if HH head employed in manufacutring
serv	serv=1 if HH head employed in services
self	self=1 if HH head is self employed
priv	priv=1 if HH head employed in private sector wage employment
pmedu	Number of adult male with Education equal to or more than primary
pfedu	Number of adult female with Education equal to or more than primary

Table A.3- continued: Quintile means of key variables, across integrated and less integrated regions

	Consumption Quintiles									
	Less Integrated Region					Integrated Region				
	Lowest	Second	Middle	Fourth	Highest	Lowest	Second	Middle	Fourth	Highest
Household Expenditure Survey 2000										
RPC (Taka)	372.17	514.83	648.38	844.08	1576.17	407.07	577.47	745.60	1016.13	2029.59
LRPC	5.90	6.24	6.47	6.73	7.30	5.99	6.36	6.61	6.92	7.51
drs	0.16	0.19	0.20	0.20	0.25	0.14	0.16	0.21	0.24	0.20
frs	0.01	0.02	0.03	0.05	0.08	0.06	0.10	0.12	0.19	0.21
Lasset	3.37	3.92	4.26	4.83	5.79	3.63	4.22	4.46	4.96	6.01
hsize	1.63	1.55	1.48	1.49	1.45	1.73	1.66	1.56	1.52	1.46
hhage	42.31	42.88	43.46	46.21	47.01	43.37	43.83	43.65	45.43	46.56
hhfem	0.09	0.07	0.05	0.07	0.08	0.11	0.09	0.11	0.12	0.12
hhmar	0.90	0.91	0.91	0.89	0.88	0.90	0.91	0.90	0.89	0.89
hedu2	0.14	0.16	0.16	0.11	0.05	0.13	0.16	0.16	0.12	0.04
hedu3	0.16	0.25	0.28	0.36	0.22	0.18	0.25	0.29	0.31	0.24
hedu4	0.03	0.07	0.07	0.16	0.16	0.02	0.06	0.09	0.14	0.16
hedu5	0.02	0.03	0.08	0.15	0.47	0.01	0.05	0.06	0.19	0.45
pchi	0.48	0.40	0.35	0.29	0.25	0.49	0.43	0.38	0.31	0.26
agri	0.54	0.53	0.46	0.48	0.33	0.44	0.41	0.40	0.31	0.19
manu	0.14	0.13	0.13	0.14	0.15	0.12	0.15	0.17	0.15	0.14
serv	0.23	0.26	0.32	0.28	0.40	0.32	0.34	0.31	0.38	0.47
self	0.31	0.45	0.50	0.58	0.57	0.34	0.42	0.44	0.50	0.44
priv	0.65	0.52	0.47	0.36	0.32	0.56	0.50	0.46	0.36	0.35
pmedu	0.85	0.87	0.95	1.28	1.74	0.95	1.05	0.99	1.32	1.70
pfedu	0.77	0.73	0.73	0.92	1.33	0.84	0.83	0.82	1.05	1.34
Household Expenditure Survey 2005										
RPC (Taka)	527.44	727.32	915.39	1217.03	2435.55	619.56	849.66	1061.90	1421.22	2765.78
LRPC	6.25	6.59	6.82	7.10	7.70	6.42	6.74	6.97	7.25	7.85
drs	0.17	0.26	0.26	0.27	0.29	0.14	0.21	0.19	0.21	0.17
frs	0.01	0.01	0.03	0.06	0.12	0.07	0.13	0.15	0.21	0.21
Lasset	2.04	2.68	3.07	3.59	4.40	2.24	2.69	3.13	3.69	4.65
hsize	1.58	1.52	1.44	1.41	1.40	1.68	1.55	1.50	1.46	1.40
hhage	42.79	43.95	45.14	46.53	47.89	42.71	44.99	46.46	46.57	47.41
hhfem	0.10	0.05	0.08	0.09	0.10	0.09	0.10	0.13	0.16	0.16
hhmar	0.88	0.92	0.90	0.90	0.88	0.93	0.91	0.90	0.89	0.89
hedu2	0.34	0.30	0.23	0.17	0.08	0.25	0.24	0.20	0.11	0.05
hedu3	0.28	0.39	0.47	0.51	0.43	0.28	0.39	0.49	0.52	0.39
hedu4	0.01	0.02	0.03	0.08	0.15	0.01	0.01	0.06	0.11	0.16
hedu5	0.01	0.02	0.04	0.10	0.27	0.02	0.02	0.04	0.12	0.34
pchi	0.44	0.39	0.32	0.28	0.24	0.49	0.40	0.34	0.30	0.25
agri	0.39	0.43	0.39	0.36	0.24	0.40	0.37	0.30	0.23	0.13
manu	0.13	0.14	0.14	0.10	0.09	0.14	0.17	0.14	0.14	0.12
serv	0.33	0.33	0.34	0.39	0.47	0.30	0.30	0.36	0.41	0.51
self	0.27	0.39	0.43	0.50	0.50	0.30	0.37	0.40	0.42	0.41
priv	0.63	0.55	0.45	0.36	0.30	0.58	0.48	0.38	0.31	0.28
pmedu	0.11	0.16	0.21	0.28	0.36	0.11	0.16	0.23	0.30	0.38
pfedu	0.11	0.15	0.19	0.24	0.34	0.10	0.16	0.22	0.28	0.39

Table A.4: Quintile means of key variables for Rural and Urban Areas

	Consumption Quintiles									
	Rural					Urban				
	Lowest	Second	Middle	Fourth	Highest	Lowest	Second	Middle	Fourth	Highest
Household Expenditure Survey 2001										
RPC (Taka)	378.35	521.15	648.95	833.58	1440.15	413.57	613.69	832.31	1206.92	2433.91
LRPC	5.92	6.25	6.47	6.72	7.21	6.00	6.42	6.72	7.09	7.70
drs	0.15	0.18	0.19	0.22	0.26	0.16	0.20	0.19	0.24	0.16
frs	0.03	0.05	0.07	0.10	0.19	0.03	0.06	0.08	0.11	0.12
Lasset	3.44	3.94	4.34	4.70	5.39	3.65	4.23	4.73	5.47	6.55
hsize	1.66	1.60	1.55	1.51	1.45	1.68	1.57	1.52	1.53	1.45
hhage	42.82	43.54	43.83	45.93	47.46	42.31	42.79	43.40	44.85	46.39
hhfem	0.09	0.08	0.06	0.09	0.11	0.12	0.09	0.08	0.08	0.11
hhmar	0.91	0.91	0.92	0.89	0.87	0.90	0.90	0.89	0.92	0.89
hedu2	0.14	0.16	0.15	0.13	0.09	0.14	0.17	0.12	0.05	0.02
hedu3	0.17	0.23	0.26	0.32	0.30	0.19	0.33	0.34	0.27	0.14
hedu4	0.02	0.06	0.06	0.13	0.14	0.05	0.09	0.16	0.20	0.14
hedu5	0.01	0.03	0.07	0.11	0.28	0.02	0.07	0.14	0.40	0.68
pchi	0.49	0.43	0.37	0.32	0.27	0.46	0.38	0.33	0.28	0.23
agri	0.62	0.60	0.53	0.54	0.47	0.13	0.14	0.14	0.10	0.06
manu	0.10	0.08	0.12	0.11	0.09	0.25	0.25	0.25	0.23	0.15
serv	0.19	0.23	0.25	0.24	0.30	0.50	0.51	0.49	0.50	0.60
self	0.33	0.46	0.50	0.59	0.63	0.31	0.35	0.39	0.36	0.38
priv	0.62	0.49	0.45	0.35	0.27	0.60	0.57	0.48	0.46	0.39
pmedu	0.91	0.90	1.00	1.13	1.43	0.89	1.00	1.30	1.79	1.91
pfedu	0.79	0.76	0.75	0.84	1.07	0.79	0.88	1.02	1.38	1.58
Household Expenditure Survey 2005										
RPC (Taka)	551.64	751.80	927.64	1191.28	2168.45	570.78	826.78	1091.48	1563.13	3176.14
LRPC	6.30	6.62	6.83	7.08	7.60	6.33	6.71	6.99	7.35	7.98
drs	0.17	0.24	0.24	0.26	0.26	0.16	0.21	0.21	0.21	0.19
frs	0.02	0.06	0.09	0.14	0.19	0.02	0.05	0.07	0.09	0.15
Lasset	2.22	2.83	3.10	3.49	4.18	1.85	2.52	3.13	4.01	4.88
hsize	1.62	1.56	1.47	1.44	1.39	1.58	1.49	1.44	1.47	1.42
hhage	43.19	44.41	46.16	47.48	49.00	42.22	43.40	44.51	44.94	46.42
hhfem	0.09	0.06	0.10	0.12	0.15	0.10	0.08	0.10	0.10	0.11
hhmar	0.90	0.92	0.90	0.89	0.87	0.90	0.91	0.90	0.91	0.90
hedu2	0.32	0.26	0.24	0.18	0.11	0.31	0.25	0.17	0.07	0.03
hedu3	0.26	0.36	0.43	0.48	0.53	0.33	0.45	0.53	0.49	0.27
hedu4	0.01	0.02	0.02	0.06	0.12	0.02	0.04	0.09	0.15	0.19
hedu5	0.01	0.01	0.03	0.06	0.13	0.02	0.04	0.09	0.25	0.49
pchi	0.46	0.40	0.36	0.31	0.26	0.44	0.35	0.29	0.28	0.25
agri	0.50	0.51	0.47	0.43	0.35	0.19	0.16	0.12	0.07	0.04
manu	0.10	0.10	0.11	0.09	0.08	0.22	0.23	0.19	0.19	0.11
serv	0.26	0.26	0.27	0.29	0.32	0.45	0.47	0.53	0.60	0.64
self	0.29	0.39	0.44	0.50	0.51	0.29	0.36	0.39	0.39	0.39
priv	0.62	0.52	0.42	0.32	0.22	0.61	0.52	0.43	0.41	0.34
pmedu	0.10	0.14	0.18	0.24	0.32	0.14	0.22	0.31	0.38	0.41
pfedu	0.10	0.13	0.17	0.21	0.29	0.12	0.20	0.26	0.36	0.43

Table A.5: Quantile Regression Results :2000

Variables	Percentiles									
	5th		25th		50th		75th		95th	
	Coef	Z	Coef	Z	Coef	Z	Coef	Z	Coef	Z
l	-0.19	-0.82	0.16	0.96	0.22	1.42	0.33	1.97	0.16	0.54
u	0.03	0.09	0.27	1.35	0.28	1.58	0.00	-0.01	-0.19	-0.55
drs	-0.02	-0.57	0.04	1.82	0.01	0.69	0.01	0.33	-0.01	-0.34
frs	0.05	0.53	0.13	2.92	0.13	3.61	0.17	2.89	0.15	1.61
Lasset	0.21	12.52	0.23	21.84	0.24	26.07	0.25	23.73	0.26	17.11
hsize	-0.34	-8.34	-0.39	-13.95	-0.47	-18.12	-0.49	-15.95	-0.49	-9.71
hhage	-0.07	-1.71	-0.03	-0.94	-0.04	-1.59	-0.03	-1.14	-0.11	-1.61
hhfem	-0.02	-0.32	0.01	0.30	-0.02	-0.42	-0.03	-0.82	0.11	1.07
hhmar	0.03	0.56	0.06	1.95	0.04	1.21	0.04	1.21	0.08	1.21
hedu2	0.08	2.88	0.04	1.86	0.06	2.89	0.04	2.12	0.06	1.50
hedu3	0.11	3.40	0.08	3.80	0.09	4.60	0.09	3.85	0.05	1.32
hedu4	0.23	4.34	0.19	7.05	0.15	5.29	0.12	2.82	0.05	0.96
hedu5	0.26	4.28	0.24	7.90	0.28	6.97	0.26	5.77	0.27	3.71
pchi	-0.23	-3.24	-0.28	-6.69	-0.24	-5.50	-0.23	-4.89	-0.41	-5.01
agri	0.09	1.19	0.04	0.97	0.03	0.88	0.04	0.69	-0.03	-0.39
manu	0.10	1.24	0.07	1.28	0.07	1.92	0.08	1.43	0.06	0.69
serv	0.13	1.63	0.11	2.30	0.08	2.15	0.12	2.25	0.06	0.84
self	-0.01	-0.10	0.02	0.41	-0.02	-0.56	-0.06	-1.03	0.01	0.15
priv	0.00	0.00	0.05	1.10	0.02	0.51	-0.03	-0.59	-0.01	-0.20
pmedu	-0.03	-1.91	-0.01	-0.67	0.01	0.75	0.01	1.21	0.03	1.67
pfedu	0.00	0.29	-0.01	-1.13	0.00	0.05	0.01	0.84	0.01	0.85
l*drs	0.10	2.45	0.05	1.94	0.08	3.11	0.07	2.23	0.09	1.75
l*frs	0.06	0.68	0.05	1.01	0.06	1.39	0.02	0.29	0.08	0.84
l*Lasset	0.01	0.30	-0.03	-1.75	-0.03	-1.89	-0.02	-1.18	0.01	0.30
l*hsize	0.02	0.28	-0.01	-0.42	0.01	0.39	0.00	0.06	-0.02	-0.34
l*hhage	0.00	0.00	0.01	0.33	0.00	0.06	-0.03	-0.74	0.03	0.39
l*hhfem	0.08	0.84	0.00	0.00	0.04	0.66	0.04	0.71	-0.19	-1.63
l*hhmar	0.13	1.68	0.00	-0.11	0.02	0.52	0.01	0.22	-0.04	-0.37
l*hedu2	0.00	-0.02	0.05	1.57	0.02	0.65	0.02	0.65	-0.05	-0.88
l*hedu3	-0.03	-0.66	0.05	1.55	0.01	0.17	0.04	1.16	0.00	-0.02
l*hedu4	-0.05	-0.69	0.02	0.49	0.00	0.06	0.03	0.46	0.06	0.76
l*hedu5	0.03	0.39	0.07	1.42	0.00	-0.06	0.07	1.22	-0.03	-0.34
l*pchi	-0.08	-0.83	-0.04	-0.70	-0.07	-1.24	-0.02	-0.27	0.00	-0.04
l*agri	0.02	0.17	-0.02	-0.35	-0.02	-0.44	-0.02	-0.32	-0.07	-0.77
l*manu	0.10	1.00	0.03	0.49	0.02	0.38	-0.01	-0.14	-0.05	-0.54
l*serv	0.03	0.30	-0.03	-0.49	0.00	0.00	-0.06	-0.92	-0.07	-0.77
l*self	-0.01	-0.08	0.00	0.09	-0.02	-0.43	0.01	0.09	-0.05	-0.75
l*priv	0.04	0.45	0.02	0.37	-0.04	-0.78	-0.01	-0.21	0.01	0.12
l*pmedu	0.02	0.78	0.00	-0.17	0.00	0.16	0.00	-0.27	-0.01	-0.57
l*pfedu	0.01	0.33	0.01	1.15	0.01	0.70	0.00	-0.24	0.03	1.16
u*drs	0.01	0.16	-0.08	-2.71	-0.08	-2.77	-0.04	-1.19	-0.03	-0.58
u*frs	0.05	0.54	-0.03	-0.58	-0.06	-1.26	-0.10	-1.75	-0.12	-1.43
u*Lasset	-0.05	-1.91	-0.04	-2.58	-0.03	-1.89	-0.01	-0.81	-0.02	-1.08
u*hsize	-0.07	-1.23	-0.14	-3.64	-0.08	-1.93	-0.04	-0.87	-0.17	-2.38
u*hhage	0.06	0.87	0.01	0.19	-0.01	-0.19	0.03	0.48	0.13	1.55
u*hhfem	-0.12	-0.98	0.00	0.03	0.01	0.21	0.05	0.92	-0.03	-0.38
u*hhmar	0.00	0.01	0.04	0.75	0.02	0.38	0.04	0.80	-0.03	-0.37

u*hedu2	-0.01	-0.20	0.06	1.42	0.05	1.36	0.04	0.90	-0.02	-0.28
u*hedu3	0.17	3.59	0.14	3.91	0.09	2.36	0.06	1.48	0.13	2.04
u*hedu4	0.08	1.14	0.15	2.82	0.16	2.69	0.16	2.73	0.10	1.08
u*hedu5	0.25	3.66	0.31	5.62	0.23	3.78	0.21	3.19	0.22	2.01
u*pchi	-0.04	-0.40	0.09	1.33	0.01	0.21	0.02	0.25	0.27	2.11
u*agri	-0.05	-0.48	-0.01	-0.14	0.00	0.04	0.02	0.32	-0.05	-0.41
u*manu	-0.11	-0.92	-0.02	-0.28	-0.04	-0.68	-0.01	-0.18	-0.11	-1.05
u*serv	-0.07	-0.70	-0.06	-1.03	-0.04	-0.70	0.00	-0.06	-0.07	-0.65
u*self	0.03	0.30	-0.07	-1.10	-0.03	-0.71	-0.04	-0.70	0.03	0.40
u*priv	0.02	0.23	-0.10	-1.67	-0.05	-1.19	-0.05	-1.05	-0.01	-0.13
u*pmedu	-0.01	-0.46	0.01	0.87	0.00	0.18	-0.01	-0.32	0.02	0.72
u*pfedu	0.03	1.32	0.02	1.25	0.02	1.50	0.01	0.79	0.01	0.44
Intercept	5.82	36.47	5.88	49.10	6.21	55.48	6.39	54.92	6.92	24.97

Table A.6: Quantile Regression Results :2005

Variables	Percentiles									
	5th		25th		50th		75th		95th	
	Coef	Z	Coef	Z	Coef	Z	Coef	Z	Coef	Z
l	0.16	0.71	0.10	0.66	0.22	1.24	0.27	1.60	0.69	2.16
u	0.04	0.17	0.02	0.13	-0.14	-0.82	-0.15	-0.80	-0.49	-1.55
drs	0.10	3.34	0.06	3.76	0.07	3.20	0.06	2.80	0.03	0.73
frs	0.25	4.04	0.31	8.04	0.34	7.14	0.38	6.20	0.65	4.77
Lasset	0.12	8.67	0.10	15.22	0.09	12.75	0.09	11.70	0.11	8.75
hsize	-0.35	-7.49	-0.35	-16.48	-0.34	-13.06	-0.37	-12.44	-0.52	-10.82
hhage	0.05	1.24	0.11	4.57	0.08	2.92	0.15	4.69	0.21	3.11
hhfem	-0.01	-0.08	-0.01	-0.42	-0.07	-1.56	-0.03	-0.60	-0.11	-1.00
hhmar	0.09	1.64	0.05	1.68	0.03	0.87	0.02	0.69	-0.03	-0.34
hedu2	-0.04	-1.36	0.00	-0.17	0.02	1.40	0.04	2.14	0.08	2.00
hedu3	0.03	0.95	0.05	2.64	0.06	2.78	0.09	3.77	0.17	3.05
hedu4	0.08	1.27	0.20	5.00	0.29	6.15	0.31	5.84	0.43	3.69
hedu5	0.12	1.61	0.23	4.99	0.30	6.81	0.41	5.77	0.52	5.24
pchi	-0.27	-3.43	-0.25	-6.84	-0.29	-6.93	-0.26	-5.83	-0.20	-2.18
agri	0.06	0.99	0.04	1.12	0.03	0.91	0.01	0.31	0.14	2.30
manu	-0.01	-0.18	0.07	1.61	0.06	1.73	0.09	1.80	0.20	3.34
serv	0.07	1.14	0.08	2.15	0.07	2.32	0.07	1.73	0.25	4.01
self	0.01	0.09	-0.03	-0.71	-0.03	-0.76	-0.02	-0.50	-0.14	-1.74
priv	-0.05	-0.75	-0.06	-1.66	-0.13	-3.38	-0.15	-2.93	-0.28	-3.39
pmedu	0.07	1.28	0.11	3.21	0.17	4.39	0.20	4.91	0.26	3.19
pfedu	-0.01	-0.09	0.13	3.08	0.18	4.41	0.28	5.90	0.23	2.87
l*drs	-0.04	-1.02	-0.05	-1.82	-0.05	-1.62	-0.08	-1.96	-0.01	-0.20
l*frs	-0.08	-1.19	-0.20	-4.33	-0.27	-5.02	-0.31	-4.56	-0.56	-3.83
l*Lasset	-0.02	-1.54	-0.01	-0.70	0.00	0.16	0.01	1.22	0.03	1.85
l*hsize	-0.01	-0.17	-0.06	-2.18	-0.01	-0.46	-0.04	-0.99	0.03	0.44
l*hhage	0.04	0.68	0.02	0.64	-0.03	-0.82	-0.02	-0.40	-0.14	-1.55
l*hhfem	-0.01	-0.08	0.06	1.34	0.14	2.84	0.07	1.20	0.08	0.75
l*hhmar	-0.06	-1.02	0.03	0.69	0.04	0.85	-0.02	-0.30	-0.04	-0.35
l*hedu2	0.04	0.96	0.06	2.34	0.04	1.59	-0.01	-0.33	-0.07	-1.15
l*hedu3	0.08	1.71	0.06	1.91	0.04	1.33	-0.01	-0.31	-0.14	-1.91
l*hedu4	0.15	1.85	0.13	2.60	0.05	0.88	-0.04	-0.47	-0.08	-0.63
l*hedu5	0.09	1.13	0.06	1.00	0.00	0.01	-0.08	-1.00	0.01	0.08
l*pchi	0.02	0.25	0.05	1.04	0.02	0.32	-0.01	-0.15	-0.07	-0.60
l*agri	-0.09	-1.26	-0.08	-1.72	-0.06	-1.31	-0.05	-0.89	-0.06	-0.72
l*manu	-0.01	-0.11	-0.02	-0.44	-0.04	-0.81	-0.07	-1.07	-0.09	-0.92
l*serv	-0.06	-0.96	-0.05	-1.25	-0.04	-1.03	-0.06	-1.21	-0.12	-1.49
l*self	0.02	0.35	0.05	0.97	0.03	0.67	0.04	0.70	0.05	0.46
l*priv	0.03	0.39	0.02	0.50	0.06	1.35	0.08	1.40	0.10	1.05
l*pmedu	0.01	0.09	0.05	0.94	0.00	-0.07	-0.01	-0.12	-0.23	-2.35
l*pfedu	-0.02	-0.22	-0.04	-0.82	-0.04	-0.85	-0.12	-1.75	-0.05	-0.47
u*drs	0.03	0.72	0.02	0.79	-0.02	-0.52	0.03	0.81	0.06	0.96
u*frs	-0.03	-0.37	0.00	-0.09	0.05	0.83	0.07	0.98	0.22	1.73
u*Lasset	-0.01	-0.33	0.03	2.62	0.04	3.95	0.04	3.58	0.04	2.71
u*hsize	-0.04	-0.70	-0.03	-1.23	-0.11	-3.51	-0.11	-2.80	-0.04	-0.54
u*hhage	-0.02	-0.37	-0.02	-0.48	0.04	0.98	0.03	0.54	0.11	1.22
u*hhfem	0.01	0.09	-0.03	-0.65	-0.05	-0.95	-0.01	-0.09	0.03	0.27
u*hhmar	0.04	0.41	0.01	0.33	-0.03	-0.53	0.03	0.58	0.04	0.46

u*hedu2	0.09	1.50	0.02	0.53	-0.02	-0.57	0.02	0.44	-0.10	-1.58
u*hedu3	0.06	0.97	0.02	0.45	0.01	0.21	0.04	0.76	-0.05	-0.57
u*hedu4	0.11	1.14	0.01	0.14	-0.04	-0.67	0.11	1.42	-0.11	-0.83
u*hedu5	0.22	2.53	0.21	3.61	0.20	3.19	0.18	1.93	-0.09	-0.71
u*pchi	-0.02	-0.24	-0.05	-0.85	0.04	0.69	0.10	1.58	0.10	0.91
u*agri	-0.08	-1.03	-0.11	-1.97	-0.11	-2.05	-0.17	-2.66	-0.29	-2.74
u*manu	0.02	0.30	-0.06	-1.04	-0.07	-1.30	-0.09	-1.58	-0.27	-2.54
u*serv	-0.01	-0.10	-0.03	-0.57	-0.01	-0.20	-0.05	-1.01	-0.22	-2.41
u*self	0.01	0.12	0.03	0.60	0.04	0.95	0.07	1.22	0.16	1.62
u*priv	0.05	0.71	0.07	1.45	0.11	2.51	0.13	2.34	0.22	2.21
u*pmedu	0.09	1.29	0.03	0.60	0.03	0.58	0.01	0.23	0.14	1.33
u*pfedu	0.11	1.36	0.04	0.83	0.08	1.57	-0.03	-0.44	0.02	0.18
Intercept	6.17	35.24	6.31	60.54	6.67	62.06	6.65	53.73	6.97	26.25
