Understanding the Sources of Spatial Disparity and Convergence

Evidence from Bangladesh

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June 2013

Abstract

This paper utilizes the mixed effects model to measure and decompose spatial disparity in per capita expenditure in Bangladesh between 2000 and 2010. It finds a significant decline in spatial disparity in urban areas and the country as a whole but no substantial change in rural areas. The decomposition analysis indicates that average years of education, the percentage of households with electricity connections, and phone ownership account

for most of the spatial variations in welfare. Spatial convergence in urban areas can be explained primarily by the expansion of electricity and phone networks for household use. Improved access to these services had little effect on spatial disparity in rural areas. This paper offers several explanations for the difference in convergence rates between urban and rural areas.

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Understanding the Sources of Spatial Disparity and Convergence: Evidence from Bangladesh¹

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Key Words: Spatial Disparity, Neighborhood Correlation, Mixed Effects Model, Infrastructure,
Sorting, Regional Convergence

JEL Classification: O18; R13; R23

¹I would like to acknowledge superb research assistance from Ieva Zumbyte. All remaining errors are mine. The views expressed in this paper are those of the author's and should not be attributed to World Bank or its member countries.

1. Introduction

The economic liberalization during the last couple of decades led to impressive economic growth and poverty reduction in many developing countries. This period has also witnessed worsening of income inequality and widening of spatial disparity (World Development Report (2009); Kanbur and Venables (2005); Kim (2008)). The rise in spatial inequality has become an important concern among policy makers in many developing countries. The widening spatial inequality in the course of rapid economic growth may not be economically inefficient if it is an outcome of increasing specialization based on comparative advantage and/or increasing returns.¹ However, spatial inequality is particularly problematic if it is primarily due to inequality of opportunities such as inequality in the provision of infrastructure, education and other services. This inequality can be argued to be of the "wrong" kind on the grounds of both economic efficiency and social desirability. From the perspective of policy making, it is thus important to know the sources of spatial disparity. In this paper, we construct a simple measure to track spatial disparity in welfare overtime. This measure can be decomposed to ascertain contributions of different factors to spatial inequality. We apply this method to examine the evolution of spatial disparity in welfare as well as its determinants in Bangladesh.

There are numerous studies documenting spatial differences in welfare in developing countries. The existing literature has taken two analytical approaches to examining spatial disparity in welfare. The most common approach is to use regression of per capita expenditure on observable household and community characteristics. The significance of area fixed effects and/or community variables in this regression is taken as an evidence of the importance of geographical location (Ravallion and Wodon (2001)). Escobal and Torrero (2005) on the other hand performed spatial autocorrelation analysis of the residual from the above regression. While these approaches can

¹The spatial inequality may be sub-optimal in the presence of agglomeration externalities even when there is no restriction on factor or goods mobility.

indicate significance of geographical differences, they do not directly provide a measure of how important those differences are or how those differences evolve over time. The second approach utilizes the local area estimation technique to estimate Theil inequality coefficients at local levels from census data and decompose the inequality index into within and between community indices (Elbers, Lanjouw, Mistiaen, Ozler and Simler (2004)). This approach however cannot be directly used to explore the factors that may lead to spatial differences in welfare, as can be done in the first approach.

This paper constructs a simple measure of spatial disparity in welfare. This measure, termed as "spatial disparity index", estimates the proportion of total variations in welfare that can be attributed to common area characteristics faced by households living in an area/community. Our "spatial disparity index" can be thought of as a spatial analog of the "neighborhood correlations" proposed by Solon, Page and Duncan (2000). The neighborhood correlations are widely used to study the influence of common neighborhood factors on the adult outcomes (e.g. education, income) of children growing up in the same neighborhood (Solon, Page and Duncan (2000), Page and Solon (2003), Raaum, Salvanes and Sorensen (2006)). To the best of our knowledge, no study has yet used this measure to study spatial inequality in welfare.

In a spatial equilibrium model, households are sorted into communities/areas in terms of income opportunities and amenities (Roy(1951), Roback(1984)). Such sorting means that households of similar attributes and hence similar welfare status tend to live in the same community, resulting in a positive correlation in income and welfare among households. At the one extreme of complete segregation or perfect sorting, all households living in a community will look similar, producing a spatial disparity index estimate of unity. In this case, all of the inequality in welfare is due to inter-community differences. In contrast, if there is no sorting, then a randomly selected sample of households from a community will be indistinguishable from a random sample of households from any other community. The difference in welfare in this case is entirely due to within

community differences (spatial disparity=0). We adopted a mixed effects model to estimate the spatial disparity index. Our empirical approach has at least two advantages. First, the spatial disparity index can be estimated from different representative household surveys to ascertain the evolution of spatial disparity over time. The magnitudes of estimated spatial disparity indices for different years can be compared to check out for spatial convergence or divergence in welfare. Second, the mixed effects model can be utilized to determine the community attributes that are important in explaining spatial differences in welfare.

The factor and non-traded goods prices in a spatial equilibrium model internalize the amenity and productivity differences among communities and household welfare – appropriately adjusted for sorting – are equated across areas. With free factor mobility, welfare differences should thus be explained mostly by household attributes. The role of opportunity becomes more prominent when labor mobility is restricted. There is now credible evidence that even when there are no formal official restrictions on labor mobility, migration is costly due to uncertainty about job search as well as travel and other personal costs (Shilpi (2011), Fafchamps and Shilpi (forthcoming), Ravallion and Wodon (1999)). Moreover, people may lack necessary human capital to switch easily between jobs (Puga (1999)). For instance, parents with relatively low human capital may end up living in a village where school access is limited and their children may not have the education and skill to avail themselves better jobs in urban areas. This inequality of opportunity will perpetuate spatial inequality overtime.

The effects of a change in opportunity on spatial disparity in the equilibrium – for instance due to investment in infrastructure and services in some locations – depend on the relative strength of "amenity" and "productivity" effects of investment. Improved access to services such as electricity not only contributes to productivity of firms/farms ("productivity" effect) but also enables households to carry out chores more efficiently ("amenity" effect). When productivity (amenity) effects predominate, spatial disparity tends to increase (decrease) in the short to medium term. In

the empirical analysis, we group observed community attributes into two broad categories: one relates to availability of infrastructure, services and agro-climatic conditions, and the other includes variables that depict possible sorting of households (human capital, employment composition etc). To emphasize the role of opportunities, we focus on basic infrastructure such as electricity, phone, sanitation etc that most households should have access. Similarly, among household attributes, we focus on human capital that relates directly to (firm) productivity. We estimate the amount of spatial difference in welfare that can be explained by each set separately and by all different sets combined together.

We analyze spatial differences in welfare in Bangladesh using two household surveys a decade apart (2000 and 2010). The study of spatial inequality in Bangladesh is interesting at least for two reasons. The country made significant strides in poverty reduction between 2000 and 2010. The poverty headcount rate fell from 48.9 percent in 2000 to 31.5 percent in 2010 (World Bank (2013)). During the same period, the incidence of poverty declined more than proportionately in traditionally poorer regions, pointing to possible narrowing of welfare gaps across regions. There is also no evidence of significant change in overall inequality over the same period. The narrowing of regional disparity is however contrary to the overwhelming evidence of regional divergence found in many developing countries (World Development Report (2009); Kanbur and Venables (2005); Kim (2008)). For policy makers in developing countries, it would be particularly useful to identify the factors that have influenced the change in spatial inequality in Bangladesh. The second interesting feature of Bangladesh is that there is no administrative restriction on either in or out migration from any region. As much of the Bangladesh's population share the same ethnicity, religion and language, there exist no serious ethnic or cultural barriers to internal migration either. The absence of major formal (official) and informal (cultural/ethnic) impediments to labor mobility implies that much of the friction in labor mobility arises from lack of infrastructure (Shilpi (2011)) and lack of human capital to facilitate movement from unskilled to skilled jobs.

Empirical evidence in this paper indicates a significant decline in spatial disparity in Bangladesh during the 2000-2010 period. More than a third of the total variance of log of per capita expenditure in 2000 can be explained by spatial factors alone compared with 26 percent in 2010. Spatial disparity declined significantly in urban areas as well (from 0.38 to 0.30). The extent of spatial disparity is much smaller in rural areas and it declined only marginally (from 0.22 to 0.20) between these years. The sustained urban-rural difference in spatial disparity is consistent with lower labor mobility due to higher skill requirements in urban jobs. The mixed effects estimation results show that much of the spatial variations in welfare (log per capita expenditure) in the pooled and urban samples in both survey years can be explained by three community level variables: average years of education, percentage of households with electricity connection, and with phone ownership. In the rural sample, agro-climatic conditions also explain a large share of inter-community variations in welfare. While electricity and phone coverage improved substantially in both urban and rural areas, such improvements had conflicting influence on the magnitudes of spatial disparity in urban and rural areas. In urban areas, expansion of electricity and phone network brought newer households under coverage whereas firms already had these connections. As a result, amenity effects predominated productivity effects and led to spatial convergence. In contrast, spatial disparity in the rural areas remained nearly unchanged suggesting that amenity and productivity effects perhaps offset each other.

The rest of the paper is organized as follows. Section 2 organized in different sub-sections lays out the empirical and conceptual framework. Section 3 describes the datasets used in the empirical analysis. Section 4 organized in different sub-sections presents the empirical results. Section 5 draws some policy recommendations.

2. Conceptual and Empirical framework

2.1 Empirical Methodology

Let Y_{ij} represents welfare of household j in community i . We assume that we can decompose welfare into three additive terms as:

$$Y_{ij} = \mu + a_i + b_{ij} \quad (1)$$

Where Y_{ij} is the welfare index (log of per capita real expenditure (LRPCE)) household j in community i , μ is the population mean of LRPCE, a_i is a community component which is common to all households in community i and b_{ij} is the household specific component for household j which captures j 's deviation from the community component. In this formulation, a_i captures effects of all common (observable and unobservable) area characteristics faced by households living in a community.

Assuming that the components a_i and b_{ij} are independent, the variance of Y_{ij} can be expressed as the sum of variances of the community and household components as:

$$\sigma_Y^2 = \sigma_a^2 + \sigma_b^2 \quad (2)$$

We define an index of spatial disparity which measures the between-community differences in welfare as:

$$\rho = \frac{\sigma_a^2}{\sigma_a^2 + \sigma_b^2} = \frac{\sigma_a^2}{\sigma_Y^2} \quad (3)$$

Where ρ measures the proportion of the variance of household's welfare that is attributable to common community/neighborhood backgrounds. Consider two households, j and k , living in community i . Using equation (1), the correlation in the welfare of these two households can be

expressed as:

$$Corr(Y_{ij}, Y_{ik}) = \frac{Cov(Y_{ij}, Y_{ik})}{\sigma_Y^2} = \frac{\sigma_a^2}{\sigma_Y^2} = \rho$$

Thus ρ also measures the correlation in welfare levels of households living in the same community. Because of this interpretation of ρ , it is also known as "neighborhood correlation (NC)" in the literature on neighborhood's influence on adult outcomes of children growing up in the same neighborhood (Solon, Page and Duncan (2000), Page and Solon (2003), Raaum, Salvanes and Sorensen (2006)). In essence, ρ is a summary statistic of common geographical attributes faced by all households in a community. A higher correlation of welfare among neighbors means that they look more like each other in many ways. This in turns implies greater spatial disparity as the welfare of the household is influenced greatly by its location. Suppose location of a household has no influence on its welfare, $a_i = 0$, $\sigma_a^2 = 0$ and $\rho = 0$. On the other hand, if location alone determines welfare of a household, then $\sigma_b^2 = 0$, and $\rho = 1$. The higher is the estimate of ρ , the larger is the spatial difference in welfare and vice versa.

In order to estimate the spatial inequality index ρ , we need to estimate the between community (σ_a^2) and within community (σ_b^2) variations. This is done by estimating a mixed effects model for equation (1). Suppose we have data for two years (t and $t + 1$). The comparison of estimates of ρ for these two years can indicate spatial convergence or divergence in welfare over these years. For instance, $(\rho_t - \rho_{t+1}) > 0$ implies spatial convergence and vice versa.

To identify the sources of spatial disparity, we utilize a more general mixed effects model:

$$Y_{ij} = \mu + a_i + b_{ij} + Z_{ij}\gamma \quad (4)$$

Where Z_{ij} is a vector of control variables. To find out the contribution of community level variables to spatial differences/inequality, we introduce various controls in the Z_{ij} vector. Consider

for example the inclusion of percentage of household with electricity connection in a community. This additional control variable can reduce the variance of Y_{ij} and reduce the estimate of σ_a^{2*} compared with the case where no control was included (σ_a^2). We can now interpret the difference between σ_a^2 and σ_a^{2*} as an estimate of the variance in the community component that can be explained by the percentage of households with electricity connections. We can also estimate the contribution of electricity connections to spatial disparity as the difference between the estimates of ρ (without any control in Z_{ij}) and ρ^* (Z_{ij} includes percentage of household with electricity connection). We can repeat this experiment by including more community level characteristics in the regressions one at a time or simultaneously. This exercise helps us to identify the sets of community level characteristics that are most closely associated with spatial variations in welfare across communities.

2.2 Sources of Spatial Disparity and Convergence/Divergence: Theoretical Insights

We rely on simple spatial equilibrium model to determine the relevant variables to be included in Z_{ij} . In a standard spatial equilibrium model, households and firms choose their location in order to maximize their welfare and profit respectively. Given endowments of natural resources (e.g. land, climatic conditions) and infrastructure and services, factor prices and prices of non-traded goods are determined in the spatial equilibrium so as to make households and firms indifferent across locations. The long run equilibrium conditions can be summarized as:

$$V_{ij}(w_i, r_i, p_{ni}; s_i) \simeq V_{hj}(w_h, r_h, p_{ni}; s_h) - M_{ihj} \quad (5)$$

$$\pi_{ik}(w_i, r_i, p_{ni}; s_i) \simeq \pi_{hk}(w_h, r_h, p_{ni}; s_h) \quad (6)$$

where V_{ij} is the indirect utility function of household j in location i , M_{ihj} is the migration

cost between location i and h , s_i is the endowment of infrastructure and services and other resources and π_{ik} is the profit of firm k . w_i, r_i and p_{ni} are wages, rents and price of non-tradeable good respectively. The equilibrium condition in equation (5) states that once household level heterogeneity is appropriately controlled for, the difference in welfare between two locations (i and h) should not exceed the cost of migration between them. Welfare levels may still vary across areas because of sorting of households (richer households clustering in the same neighborhood and vice versa). But once we control sufficiently for household sorting and possible migration costs, the spatial difference in welfare (ρ) should become small and perhaps insignificant in magnitude in the long run equilibrium. Thus an important set of controls to be included in Z_{ij} is the vector of variables reflecting heterogeneity of household attributes across locations.

The sorting of households as well as the prices of goods and factors at different locations are however outcomes of the relative attractiveness of the locations. The attractiveness of a place is determined by its natural endowments of land and geo-climatic conditions, and availability of infrastructure and services. The basic determinants of ρ are thus differences in the endowments of natural resources and provision of infrastructure and services (s in equations 5 and 6). To examine the extent to which spatial disparity is determined by these basic locational attributes, we included a set of variables indicating access to basic infrastructure and services as well as geo-climatic conditions in Z_{ij} . We focus specifically on those basic infrastructure and services variables that every household should have access to (e.g. electricity). If these basic infrastructure/services are provided equally across locations to ensure "equality of opportunities", then they should not be sources of spatial difference in welfare.

The equilibrium condition in equation (5) allows welfare between two locations to differ due to costly migration. Migration cost is not the only friction in labor mobility. As emphasized in Puga (1991), lack of skilled workers can sustain welfare differences across areas. For instance, urban jobs often require specialized skills which rural workers may lack. This leads to greater

welfare differences between urban and rural areas compared with differences implied by migration costs alone.

How does a change in infrastructure or services coverage affect spatial disparity? Consider the case when electricity connection is given only to firms in community i . The availability of electricity facilitates automation of production leading to significant reduction in costs. As more firms locate in i to take advantage of lower costs, equilibrium conditions in equations 5 and 6 imply that wages, rents and non-traded prices will rise and more households will move to location i . This could result in an increase in ρ due to rise in factor prices and greater sorting of households across communities in the short to medium term.

Now consider the case where additional households are brought under the coverage of electricity in village i . Since households derive positive utility from being able to read newspapers, watch TV and run appliances, this increases V_i at the initial price vector, leading to more households moving to village i . In the new equilibrium, rent and price of non-traded goods will rise, and wage fall (as households are willing to forego wage to get extra utility from electricity) in location i . Prices and wages in all other locations will move in the opposite direction. As a result, welfare differences across locations (ρ) will be smaller in the short to medium term, though in the long run equilibrium, welfare differences between locations should not exceed the migration costs between them.

If both households and firms receive benefits from electricity connections at the same time, its effect on spatial disparity in welfare will depend on the strength of the "amenity effect" on households relative to that of "productivity effect" on firms, while both rents and prices of non-traded goods will rise, and there will be more concentration of households and firms in i . Investment in the provision of infrastructure and services can thus have non-linear effect on spatial disparity in welfare.² Another important source of non-linearity is that once all households in

²Puga(1991) illustrates additional channels through which expansion of road transport for instance can initially

the country have electricity connections as observed in most developed countries, then electricity connections should not be a source of spatial disparity any more though intensity of electricity use may still vary with households' incomes.

2.3 Empirical Estimation

In the empirical estimation, we follow the practice of existing literature and use log of per capita real expenditure as an indicator of welfare (V_{ij}). Per capita household expenditure is deflated by the spatial cost of living index. We estimated spatial disparity indices for two years (2000 and 2010). The indices are also estimated by including or excluding different sets of controls for household attributes (sorting) and locational attributes (infrastructure and geo-climatic conditions). Suppose $\rho(s)$ denotes the spatial disparity arising from differential provision of infrastructure, and $\rho(H)$ from sorting of household attributes. Estimates of $\rho(s)$ [$\rho(H)$] for two years can be compared to find out how much of the spatial convergence or divergence is due to change in provision of infrastructure and services [sorting of household attributes]. Because of the fundamental differences in the economic structure of urban and rural areas, estimations of spatial disparity are done separately for rural and urban areas along with that for the entire country ("pooled sample").

3. Data

The main data sources for our empirical analysis are the two rounds of the Household Expenditure Survey (HIES) of Bangladesh. The survey rounds utilized in this paper are 2000 and 2010.³ Both of the surveys were carried out by the Bangladesh Bureau of Statistics with assistance from the World Bank. Both surveys utilized a two-stage stratified sampling strategy to select a nationally representative sample. There were 14 strata in 2000 survey and 16 in 2010 survey. The total sample sizes are 7,440 households from 442 primary sampling units (psus) in

lead to more spatial concentration followed by regional convergence at even lower level of transport costs.

³The HIES was done for 2005 also. The results based on 2005 data are very similar to those using 2010 data. We omitted analysis for 2005 round of HIES for brevity.

2000 and 12,240 households from 612 psus in 2010. The clustered sampling used in both surveys means that households living in a psu are close to each other and can be assumed to live in the same community or neighborhood.

To provide a sense of how far/close households in a psu live, we briefly discuss the sample design in relation to population density in Bangladesh. For the 2010 survey, the psus were selected randomly from the integrated multi-purpose survey (IMPS) framework developed by the Bangladesh Bureau of Statistics. The IMPS identified 1,000 psus using the 2010 population census as the frame. The psu borders are defined to be contiguous census enumeration blocks (usually about 2) and consisted of 200 households. At the first-stage of sampling, psus are selected randomly from the IMPS sample of 1,000 psus. At the second stage, 20 households are selected randomly for each psu. The sample design in 2000 is slightly different. At the first stage of sampling, psus are selected randomly using population weights from the 2000 population census. At the second stage, 20 households were drawn for each psus in rural and non-metropolitan urban areas and only 10 households were drawn from each psu in metropolitan areas.

The population density in Bangladesh is the highest among all non-city state countries in the world. According to the 2010 census, the population density in Bangladesh is 1,015 per square kilometer (sq. km). If all of world's current population were squeezed into USA, the density would be 670/sq km, or into Australia, the density would be 835/sq. km (Streatfield and Karar, 2008). The density is smaller in rural areas, about 764/sq km. With an average household size of 4.4, this implies that each rural psu in 2010 has on average an area of little over 1 sq km. The population density in urban areas (8940/sq km) is many times higher than that in rural areas. On average, more than 2,000 households live in an area of 1 sq km in urban areas. Thus our psus in urban areas cover perhaps no more than a city block. The population density in 2000 was about 880/sqkm, implying that geographical areas of 2000 HIES psus were slightly larger than that of 2010 psus. Yet, in both survey years, households in a psu lived in close proximity to each other.

The HIES 2010 is a balanced survey with a fixed number of households (20) in each psu, making estimation of spatial disparity index simple. The metropolitan strata of the 2000 survey has fewer households (10) relative to rest of the survey stratum. Since a psu with 20 households contains more information than one with 10 households, one can use an appropriate weighting scheme to correct for the unbalanced nature of 2000 survey. Solon, Page and Duncan (2000) proposed three such weighting schemes. As the proportions of our sample from metropolitan stratum are small, the results are not sensitive to weighting schemes. Thus we use equal weighting for all psus in both of the survey rounds.

The survey collected a wealth of information on many aspects of living standards including detailed household level expenditure, demographics, employment, education and housing characteristics. We utilized these surveys to define employment composition, education levels, and other community level infrastructure and service provision variables. We also constructed several spatial price indices from the survey data. While HIES data can be used to generate many community variables, the datasets do not have information on geographical attributes of the communities. We collected information on agro-climatic conditions and distances to cities from other data sources. Rainfall data are drawn from Bandyopadhyay and Skoufias (2012). The original data on rainfall come from the Climate Research Unit (CRU) of the University of East Anglia. The CRU reported estimated monthly rainfall for most of the world at the half degree resolution from 1902 to 2009. The CRU estimation combines weather station data with other information to arrive at the estimates.⁴ To estimate the sub-district (upazila/thana) level rainfall from the CRU data, Bandyopadhyay and Skoufias (2012) uses area weighted averages.⁵ Travel times to different

⁴Previous versions of the CRU data were homogenized to reduce variability and provide more accurate estimation of mean rain at the cost of variability estimation. The version 3.1 data is not homogenized and thus allows for better variability estimates. The estimates of rainfall near international boundaries are not less reliable as compared with those in the interior of the country, as the CRU estimation utilizes data from all the weather stations in the region.

⁵For example if an Upazila/thana covers two half degree grid cells for which CRU has rainfall estimates, then upzila/thana rainfall is estimated as the average rainfall of the two grid-cells, where the weights are the proportion of the area of the upazila/thana in each grid-cell. For details, please see Bandyopadhyay and Skoufias(2012).

destinations were computed using GIS software. Data on agro-ecological zones are drawn from the Bangladesh water board database.

Table 1 reports the incidence of poverty and extent of inequality during the decade covered by the two surveys. The incidence of poverty is measured by the head count ratio which was in turn determined from an official poverty line decided by the Bangladesh government. The estimated head count ratio shows a significant decline in poverty in Bangladesh from 49 percent in 2000 to 35 percent in 2010. Poverty declined substantially in both urban and rural areas. Poverty incidence is much lower in urban areas compared with rural areas. The inequality in per capita expenditure measured by the Gini coefficient shows that inequality at the national remained nearly unchanged during this decade (Gini=0.31 in both survey years). Inequality in urban areas declined somewhat, from 0.37 to 0.33 between the survey years, but it has started to inch up in rural areas.

The summary statistics from the surveys reported in appendix table A.1 show considerable increase in per capita expenditure between 2000 and 2010. Among the variables representing access to infrastructure, the proportion of households with electricity and phone showed dramatic changes between these two years. The average education level of the workforce has increased though only in rural areas. Employment pattern has become more diverse in rural areas and more specialized in urban areas. For instance, agriculture's share in rural employment fell from 65 percent in 2000 to 53 percent in 2010. Urban employment has become more concentrated in manufacturing and service activities. The differences between rural and urban areas in most measures are evident for both survey years with rural areas trailing behind urban areas.

4. Empirical Results

Our estimation of spatial disparity index is based on equation (4). In all different specifications of equation (4), age dummies for the household head and his/her gender are included as controls.

We then introduce other control variables one at a time, and then simultaneously. We divide the controls into three different sets: (i) variables indicating agro-climatic endowments; (ii) variables indicating access to infrastructure and services; and (iii) variables depicting locational sorting of households. The mixed effects model specified in equation (4) is estimated using the Restricted Maximum Likelihood (REML) technique which is implemented by the *xtmixed* command in Stata. The spatial disparity coefficient (ρ) and its confidence intervals are estimated by applying the *NLCOM* command after the mixed effect estimation. All estimations are done for the full sample and for rural and urban samples separately. We also perform several robustness checks.

4.1 Spatial Disparity in Welfare

We start with the result from our simplest specification of equation (4) which included no controls other than age and gender dummies for the household head. This base line estimate of spatial disparity in the pooled sample is 0.363 in 2000 and 0.266 in 2010. The estimate for 2000 implies that more than a third of the variations in log of per capita consumption can be explained by location alone. The spatial differences in welfare narrowed considerably in 2010 as just above a quarter of variations in LRPCE can be attributed to location alone. The spatial disparity in urban areas is much higher in both years compared with that in rural areas. The estimates for urban areas indicate considerable decline in disparity between 2000 and 2010 -from 0.385 to 0.298. The estimates of spatial disparity indices for rural areas – 0.218 in 2000 and 0.199 in 2010 –are smaller in magnitudes compared with urban areas and they declined only slightly between these two years. Table 2 reveals a trend of strong spatial convergence in welfare within urban areas and in the country as a whole during the decade of 2000.

The lower panels of Table 2 report estimates of the spatial disparity indices when agro-climatic controls are added separately and simultaneously (last panel). In the results reported in panel B, Z_{ij} vector included average annual rainfall over 30 years (1980 to 2009) as a control. Inclusion of

this variable did not affect the estimates of spatial disparity perceptibly. The estimates remained nearly unchanged when we instead included the standard deviation of rainfall over the 30 year period as a control (panel C). In panel D, we included variability of monsoon rain as a control. The variability of monsoon rainfall is measured by the coefficient of variation of total rainfall for the monsoon season of June-September over the 30 year period. Higher variability of rainfall is significantly and negatively correlated with LRPCE in rural areas (appendix table A.2). But its effects on the sizes of spatial disparity indices are still small (panel D) in both survey years.

Next, we included a set of dummies to indicate the agro-ecological zones where those zones were determined by agricultural scientists on the basis of elevation, flooding possibility, land quality, soil moisture and rainfall variability etc. The country has 17 distinct agro-ecological zones. Our data on agro-ecological zones come from the early 1990s. Since then, several new sub-districts have been created. For these newly created sub-districts, the agro-ecological zone information is missing and we capture this by introducing a dummy. The estimates of spatial disparity after controlling for agro-ecological zones (panel E) are considerably lower than the base line estimates (panel A). For instance, agro-ecological zones explain about 13 percent of inter-community variations in LRPCE in 2000 and 11 percent in 2010. The corresponding estimates for rural areas are 12 percent in 2000 and 17 percent in 2010. In the final panel (F), both agro-ecological dummies and variability of annual and monsoon rainfall are introduced as controls. As these two types of controls can explain considerable variations in LRPCE, the estimates of spatial disparity declined for all three samples in both years.

4.2 Access to Infrastructure and Services

In this sub-section, we focus on some basic infrastructure and services that households living in a community should have access to but may not have it yet. We analyze differences in access to electricity, phone, sanitation, safe drinking water and to large urban markets across communities.

It should be noted that all access variables are defined as the proportions of households in the community that have access to that infrastructure or services. These access variables are intended to capture inequality of opportunity, as we are focusing on basic infrastructure and services that every household should have access.⁶ As before, we first add each access variable separately in order to explore their individual contributions to spatial difference in welfare, and then add all of the variables simultaneously. The estimates of neighborhood correlations from these experiments are reported in Table 3. The regression coefficients from these experiments are reported in appendix table A.2. The topmost panel in Table 3 reproduces the baseline estimates for the ease of comparison.

First, we consider access to electricity. On average, 37 percent of the households in 2000 and 58 percent of households in 2010 had access to electricity (appendix Table A.1). While 84 percent of urban households had electricity connections in 2010, only 42 percent of rural households had the same in 2010. Access to electricity improved substantially in rural areas between the two survey years as proportion of households with electricity has more than doubled. Panel B in Table 3 reports the estimates of spatial disparity indices when we control for the proportion of households in a community with access to electricity in the regression. The estimates become significantly smaller compared with our baseline estimates in all three of our samples and in both survey years. The estimate for the full sample in 2000 declines from 0.363 in the baseline to 0.231 when access to electricity is added as a control. This means that electricity connection's absolute contribution to spatial disparity is 0.13 which is about 36 percent of the baseline estimate of spatial disparity. The regression coefficients reported in table A.2 shows that LRPCE is positively and significantly correlated with households' access to electricity in both survey years and for all three samples.

⁶One can argue that access variable also reflects the fact that more households living in a poorer community may not be able to afford to – for instance – use electricity. Equality of opportunity on the other hand requires that every household should have electricity connection regardless of their location whereas intensity of electricity use may depend on a household's income not its access.

The results suggest that access to electricity matters significantly in determining the size of spatial disparity.

Between 2000 and 2010, there has been dramatic improvement in access to phone due mainly to rapid spread of cell/mobile phones. Before the advent of cell phones, only 2 percent of households reported to having a phone connection in 2000. By 2010, the proportion had increased to 65 percent. Even in rural areas, 57 percent of households reported to possessing a phone in 2010. We report the estimates of spatial disparity indices in panel C of table 3 when we added the percentage of households in a community with phone (cell and landline) ownership. The inclusion of this variable in the estimation of equation (4) leads to a significant decline in the magnitudes of spatial disparity indices. The decrease is largest in the urban sample. For instance, inclusion of the phone variable decreases the estimate of the spatial disparity index in urban areas from 0.30 in our baseline case to 0.16 in 2010. These estimates imply nearly a 45 percent decline in the magnitude of spatial disparity index. The contribution of phone ownership to spatial disparity ranges from 0.05 (rural) to 0.134 (pooled) in 2010. The estimates of regression coefficients in appendix table A.2 indicate a strong, positive and statistically significant association between LRPCE and proportion of households with phone ownership. The phone ownership variable is somewhat less effective in explaining the inter-community variations in LRPCE in rural areas compared with urban areas in 2000 primarily because less than one percent of rural households had a phone connection in that year.

Along with access to electricity and phone, we check if any other measure of access to infrastructure and services can also help to explain spatial disparity as well. Panels D, E and F of Table 3 report the results when access to market, sanitation and safe drinking water are introduced separately in the regressions. The surveys did not collect information on distance to markets and cities from the households. We estimate these distances using a mid-1990s roadmap. The location of survey psus are also unknown. Thus estimated travel times are from the center

of the sub-district (upazila/thana) where a community is located to major urban cities. We estimated travel time to two main centers of economic activities in the country: the capital city Dhaka (population more than 10 million) and the port city of Chittagong (population more than 4 million). We also estimated travel time to the nearest city of 100 thousand or more population.⁷ Access to sanitation is measured by a set of variables indicating the proportion of households in a community with access to different types of sanitation offering differing degrees of protection.⁸ Access to safe drinking water is also measured in a similar way. While the regressions show statistically significant correlations between LRPCE and different access variables with expected signs, only access to sanitation appears to have an influence on spatial disparity comparable to access to phone or electricity. Summary statistics in table A.1 indicate considerable improvement in access to sanitation⁹ as the percentage of households using open fields or temporary earthen structures as toilets fell from 44 percent in 2000 to 23 percent in 2010. In contrast, more than 95 percent of households in Bangladesh had access to safer drinking water mostly from tubewells by 2000. Similarly our measure of distance has no time variation due to lack of access to data on new road construction and improvement.

Panel G of Table 3 reports the estimates of spatial disparity indices when all infrastructure and services variables are introduced simultaneously in the estimation. The results show that infrastructure variables do account for a large share of neighborhood correlations. In the pooled sample, infrastructure and services variables account for 59 and 42 percent of spatial disparities in 2000 and 2010 respectively. In the urban sample, their contribution to spatial disparity is even larger; 71 percent in 2000 and 56 percent in 2010. In the rural sample, these variables account

⁷Note that these travel time estimates do not fully reflect the actual travel time from our neighborhoods/communities to urban centers and hence should be taken as rough indicator of actual distances.

⁸The HIES surveys for both years collected information on types of toilets/latrines used by the households. The surveys made distinction among six different types of latrines with sanitary latrine being one of them. Rest of the categories indicate different degrees of sanitation afforded by the latrines – from cemented water-seal latrines to open fields (no protection).

⁹The use of complete sanitary toilets increased only slightly over the decade though there has been considerable increase in the use of toilets that provide some measure of sanitary protection.

for almost a third of spatial disparities. In the final panel of Table 3, we report the estimates of spatial disparity indices when geo-climatic features of communities are added. The resulting estimates of spatial disparity indices are much smaller even compared with those in panel G. The geography and infrastructure indicators account for 50, 60 and 45 percent of spatial disparities in pooled, urban and rural samples respectively in 2010. Consider the estimates for the rural sample in 2010. The geography variables alone account for 18.8 of spatial disparities, infrastructure variables alone for 28.7 percent. These two sets of variables together can explain 45.4 percent of spatial disparity. These estimates suggest that the overlap between agro-climatic conditions and infrastructure and service provision is not large in rural areas. In other words, provision of infrastructure and services is not necessarily targeted to areas with better agro-climatic potential in Bangladesh. This is consistent with the evidence reported in Deichmann et al (2008).

Many of the infrastructure variables are likely to be correlated with each other. We check the regressions underlying the spatial disparity index estimates in the last panel of Table 3.¹⁰ Despite the possibility that potential correlations can make individual coefficients statistically insignificant, we find access to electricity and phone to be highly statistically significant with expected positive signs in all regressions.

4.3 Sorting of Households

In the case of sorting of households, we focus on key indicators of human capital and employment compositions. The estimation results are reported in Table 4.

We start with sorting of human capital across communities. We define average years of education of the working age population in the community as an indicator of human capital. If households are sorted across communities in terms of their human capital, then average education level should vary significantly across communities, and this should be able to explain variations in

¹⁰These regression results are omitted for the sake of brevity.

income and hence welfare.¹¹ Panel B of Table 4 reports the estimation results when the average education level of the community is added as a control. The large decline in the magnitudes of spatial disparity indices compared with baseline estimates (panel A) indicates that households are indeed sorted across areas in terms of human capital. The sorting of human capital matters most in urban areas where nearly 60 percent of spatial disparities in 2010 can be explained by education differences. Difference in education level matters much less in rural areas as only small fractions (e.g. 12.5 percent in 2010) of spatial disparities are due to educational sorting. This is not surprising given that much of the economic activities undertaken in rural areas do not require higher education (e.g. agriculture, trading etc). As anticipated, LRPCE is positively and significantly correlated with education level (appendix Table A.2).

Panels C and D report the results when we control for skill and sectoral composition of labor force respectively. Using occupational classification of jobs, we define three skill categories. Skilled workers consist of professional workers (e.g. doctors, teachers, engineers, writers etc). Semi-skilled are those engaged in production and services activities that require some skill (e.g. clerks, production workers in manufacturing etc). The omitted category of unskilled workers consist of those who are employed mostly as agricultural workers or services workers (e.g. domestic services). Sectoral compositions are represented by proportion of the labor force employed in manufacturing, and in services activities.¹² The inclusion of either set of controls leads only to a modest decline in the estimates of spatial disparity indices. The employment composition variables are defined at a much broader sectoral and skill categories which may explain why they account for a small part of spatial disparity. The regressions reported in panel E include employment and human capital controls simultaneously. The estimates in panel E are nearly indistinguishable from those in panel B where only education level was controlled.

¹¹To the extent education and ability are positively correlated, education variable should capture some of the ability sorting as well.

¹²Agriculture is the omitted category.

To see if households are sorted across communities in terms of demographics also, we include community level average dependency ratio (defined as the ratio of the total number of children over household size) as an explanatory variable. Addition of this variable reduces the magnitudes of the spatial disparity indices modestly in both survey years. Panel G reports the results when human capital, employment and the dependency ratio are included simultaneously. The estimates of the spatial disparity indices are comparable to the estimates in Panel B. Once education differences are controlled for, sorting of other household attributes (e.g. employment, or demographic factors) accounts for only an insignificant part of neighborhood similarities. The final panel in Table 4 reports the results from regressions which controlled for geographic factors in addition to all indicators of household attributes considered so far. The results show that household attributes (mainly education) and geographic factors together can explain away 67 percent of spatial disparity in urban areas, 52 percent in the pooled sample and 34 percent in the rural sample in 2010.

4.4 Infrastructure, Sorting and Spatial Disparity

Table 5 reports the results when we introduced different sets of controls discussed above in different combinations. Panel B reports the estimates of spatial disparity indices when all infrastructure and services related variables and all household attributes are introduced simultaneously. Panel C reports the results when we add geographical controls in addition to the controls introduced in panel B regressions. An important concern in the estimation of spatial disparity is that the cost of living indices are constructed at a fairly aggregate geographical unit level (stratum levels in both surveys). Such aggregate costs of living may not be able to capture the finer variations in the cost of living across our communities. To see if this is so, we define three price indices. An index of housing cost at district level is estimated using a hedonic regression that controlled for housing characteristics. We construct a rice price index at the community level which also nets out the quality differences. To get an idea of the prices of non-traded goods, we regress the wages

of workers employed in services activities on worker characteristics and district fixed effects. The non-traded price index is constructed from the district fixed effects of this regression. The results from the regressions that added these prices as regressors are reported in the last panel of Table 5.

Table 5 reveals several interesting patterns in spatial disparity. First, infrastructure and household attributes can account for the majority of spatial variations in LRPCE in urban and pooled samples. Second, agro-climatic conditions are more important in rural areas explaining about 20 percent inter-community variations in LRPCE. Third, adding disaggregated information on living cost leads only to a marginal decline in the magnitudes of estimates of spatial disparity indices. Thus cost of living differences beyond what is accounted for by the spatial price index do not appear to be a major source of spatial disparity. Finally, when all explanatory variables are included in the regressions, the resulting estimates of spatial disparity indices are small in both survey years. For instance, the highest and lowest estimates of neighborhood correlations are 0.094 for rural areas in 2010 and 0.043 for urban areas in 2000. Our estimates suggest that the set of controls in the regressions can successfully explain most of spatial variations in welfare in all three samples and in both survey years.

The results suggest interesting differences between urban and rural areas. The combined controls for household attributes and infrastructure variables can explain most of the spatial disparities in urban areas in both survey years. For instance, infrastructure and sorting controls can account for 85 percent of neighborhood correlations in 2000 and 73 percent in 2010. When agro-climatic controls are added, these explanatory variables can explain 87 percent of inter-community variations in LRPCE in 2000 and 75 percent in 2010. The infrastructure related variables alone can explain 71 percent of spatial variations in LRPCE in 2000 and 56 percent in 2010 (Table 3). On the other hand, household attributes alone can account for 57 and 61 percent of spatial disparity in 2000 and 2010 respectively (Table 4). The estimates in Table 5 confirm

that there is considerable overlap between infrastructure and household attribute variables. This is expected as sorting of household attributes is supposed to be outcomes of attractiveness of communities in terms of access to infrastructure and services as well as agro-climatic conditions. What is interesting to note is that though the handful of infrastructure and geography variables can explain a significant proportion of spatial variations in LRPCE, the overlap between these variables and household attributes is not complete.

In contrast to urban areas, the explanatory variables are less successful in explaining spatial differences in welfare in rural areas in either years. This is partly because sorting of human capital is less important in rural areas where agriculture predominates. Though regressions control for agro-climatic conditions, these measures are defined at much larger spatial resolutions due to lack of information on micro agro-climatic conditions at the community level. More importantly, one would expect access to market to have larger roles in rural areas but our measure of distance is again defined at sub-district level and does not capture recent improvements in road transport.

To provide an indication of which of the individual regressors are important in explaining spatial variations in welfare, we report the regression results from the mixed effects model in Table 6. The regression results highlight importance of three variables in explaining spatial variations in LRPCE. These are education level, access to phone and electricity. The coefficients of these three variables are large in magnitudes, positive in sign and highly statistically significant in all of the six regressions. Note that access to electricity and phone are statistically significant even after controlling for possible indicators of sorting and income such as education and skills. While wealthier community may be argued to have better access to these services due to income effect, the regression results suggest direct influence of electricity and phone connections beyond what would have been possible if it were due only to income effect.

4.5 Sources of Spatial Convergence in Welfare

To explore the sources of change in spatial difference in welfare, we draw from the estimates

reported in Tables 3, 4 and 5. The top row in Table 7 reproduces the estimates from the base case (top panel, Table 2). As already noted, these base line estimates suggest strong spatial convergence within urban areas and in the country as a whole while no substantial change in rural areas.

The estimates in Table 3 can be used to compute the contribution of infrastructure and geo-climatic variables to spatial disparity. The estimate for urban areas in 2000 is for example computed as a difference between the baseline estimate in panel A and estimate in panel H in Table 3. This estimate of infrastructure and geography’s contribution can be taken as the total (upper bound) contribution including its direct and indirect effects on productivity and sorting. We compute the contribution of sorting by taking the difference between estimates in panel A (baseline) and panel G in Table 4. We also compute the lower bound estimates for the contribution of infrastructure and sorting to spatial disparity. We define the lower bound for infrastructure’s contribution as equal to baseline estimate (ρ in Table 7) minus portion that remains unexplained by observed attributes (v) and the portion that is explained by sorting alone (ρ_2). This estimate sets the contribution of sorting at its highest level, and nets it out from the joint contribution of sorting and infrastructure to spatial disparity. This is a lower bound estimate because a large part of sorting itself is outcome of differential infrastructure provision. We use the same methodology to estimate a lower bound estimate for the effect of sorting on the magnitude of spatial disparity indices. Because the patterns of spatial convergence are different between rural and urban areas, we discuss them separately.

In urban areas, the decline in neighborhood correlations between 2000 and 2010 is mirrored by the decline in infrastructure’s contribution to neighborhood similarity. For instance, spatial disparity within urban areas fell by 0.086, nearly a 22.5 percent decline from its 2000 level. The contribution of infrastructure and geo-climatic variables declined by 0.10 from 0.285 in 2000 to 0.181 in 2010. Even the lower bound estimates imply a considerable decline in neighborhood

correlations due to a decline in the role of infrastructure. In contrast, both upper and lower bound estimates imply a somewhat smaller contribution of sorting to overall declines in spatial disparity. The declining contribution of infrastructure related variables to spatial disparity is expected when there is significant expansion in access to infrastructure. Summary statistics (table A.1) show significant improvement in both phone and electricity access in urban areas. The improved access to infrastructure reduced spatial disparity by making infrastructure differences less important for explaining neighborhood similarity. The effect of expansion of infrastructure on the magnitude of spatial disparity is consistent with predominance of "amenity effect" over "productivity effect" discussed in the conceptual framework. For example, at the early stage of expansion of electricity, commercial use is given priority over household use. Indeed all of our urban psus have electricity in both survey years. Further expansion of electricity brought more households under coverage, and thus favored household use of electricity. This may explain why improved infrastructure provision led to only modest increase in sorting and substantial decline in spatial disparity in welfare in urban areas.

The estimates for rural areas imply a small decrease in spatial disparity. In contrast, the spatial disparity attributable to infrastructure has increased by a small amount in rural areas. As a result, infrastructure related variables explain a larger share of spatial disparity in 2010. The summary statistics show significant improvement in access to basic infrastructure (electricity, phone, sanitation) in rural areas. The improvements (e.g. electricity, sanitation) – though starting from a lower base – were in some instances much larger in magnitude than that in urban areas. That such improvements left spatial disparity nearly unchanged in rural areas is puzzling at first sight. However, as shown in the conceptual framework, the effect of better access to infrastructure on spatial disparity depends on the relative strength of its amenity and productivity effects. The results for rural areas are consistent with the case where these two effects nearly offset each other. Despite improvements in coverage of electricity, phone and sanitation, the percentage households

with access to these infrastructure and services in rural areas are still much smaller than that in urban areas. For instance, coverage of electricity in rural areas is still lower than that in urban areas ten years ago. An improvement from such a low base case is expected to increase spatial disparity as productive uses of infrastructure may get priority over its use as household amenity. We do find a somewhat larger role of infrastructure related variables in explaining rural spatial disparity. Another source of the contrasting evidence for rural areas is that the geographical and infrastructure related variables included in the analysis explains relatively small share of spatial disparity. As noted before, we do not have data on improvement in road transport which is expected to be more important in explaining disparity in rural areas.

The results for our pooled sample also indicate spatial convergence between 2000 and 2010. The results for pooled sample are similar to those from urban samples. The reduction in spatial disparity in this case is due to both decrease in infrastructure and household attributes' roles in inducing neighborhood similarity.

Finally, we find greater spatial disparity in urban areas and in the country as a whole compared with rural areas. The physical costs of migration are unlikely to vary substantially between urban and rural areas. The greater spatial disparity in urban areas points to the presence of an additional barrier to labor mobility. Urban jobs require specific skills which may not be available in other areas. This skill constraint could provide an explanation for greater spatial disparity in urban areas, and between urban and rural areas.

5. Conclusions

Recent years have seen a resurgence in interest in identifying appropriate policy responses to spatial inequality in developing countries. This resurgence is driven by the rising regional inequality and resulting social tensions during the post liberalization period in a large number of developing countries. To design policy responses, one must understand the sources as well

as evolution of spatial disparity. This paper constructs a measure of spatial disparity which can be tracked overtime. More importantly, we introduce a decomposition analysis which can discern the relative influences of access to infrastructure and services and household attributes on spatial disparity. The spatial disparity index estimated and analyzed in this paper is comparable to "neighborhood correlations" widely used to study impact of childhood environment on adult outcomes (Solon, Page and Duncan (2000), Page and Solon (2003), Raaum, Salvanes and Sorensen (2006)). To the best of our knowledge, no study has yet used this measure to study spatial inequality in welfare.

This method is applied to measure and decompose spatial disparity in welfare in Bangladesh which made great strides in reducing poverty during the last decades. Empirical estimates based on two rounds of Household Income and Expenditure Surveys 2000 and 2010 suggest significant spatial convergence in living standards in urban areas and in the country as a whole. The extent of spatial disparity is lower in rural areas compared with urban areas and there has been no significant change in rural areas during the decade. The sustained differences in the magnitudes of spatial disparity between rural and urban areas is indicative of slower mobility of workers across rural and urban activities due to skill constraint. Our results also show that welfare differences across communities in both survey years can be explained mostly by three community level factors: average years of education, percentage of household with electricity, and with phone. In rural areas, agro-climatic conditions are also important for explaining welfare variations across communities. These results show that a large part of variations in welfare in Bangladesh is indeed due to unequal distribution of basic opportunities (e.g. electricity).

Between 2000 and 2010, households in both urban and rural areas experienced significant improvements in access to basic infrastructure and services such as electricity, phone and sanitation. The decline in spatial disparity in urban areas is due mainly to improved infrastructure access with sorting of educated workers playing a smaller role. We find the opposite in the case of rural

areas. The convergence in urban areas is consistent with the predominance of amenity effect of infrastructure where improved infrastructure coverage favors its use for household activities. In contrast, arrival of new infrastructure (e.g. electricity) appears to have both "productivity effect" in terms of reducing production costs of firms/farms, and "amenity effect" due to household use. The evidence for rural areas is consistent with the case where these two effects offset each other so as to leave spatial disparity nearly unchanged.

Two interesting policy conclusions follow from the empirical analysis. To reduce spatial differences between urban and rural areas, countries with no formal and informal restrictions on migration should pay more attention to investment in education and skill formation. Such investment should facilitate mobility of workers to skilled jobs. Our results also suggest a way to deal with the rising regional inequality during the post-liberalization period. To keep regional inequality in check, investments in infrastructure and services benefitting firms/farms should be balanced by investments benefitting households. For basic infrastructure such as electricity, this means providing it not only to firms/farms for productive use but also to households for its amenity value.

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Table 1: Poverty and Inequality in Bangladesh, 2000-2010

	Poverty		Inequality	
	Head Count Ratio		Gini Coefficient	
	2000	2010	2000	2010
National	49	32	0.312	0.308
Urban	35	21	0.374	0.336
Rural	52	35	0.274	0.282

Source: Bangladesh Poverty Assessments, different reports

Table 2: Spatial Disparity and Geo-climatic conditions

	2000			2010		
	All	Urban	Rural	All	Urban	Rural
Base Case						
Neighborhood Correlation (ρ)	0.363*** (19.929)	0.385*** (13.271)	0.218*** (11.820)	0.266*** (20.405)	0.298*** (12.998)	0.199*** (14.158)
Controlling for 30 years average rainfall						
Neighborhood Correlation (ρ^*)	0.360*** (19.814)	0.384*** (13.216)	0.218*** (11.803)	0.266*** (20.367)	0.289*** (12.734)	0.199*** (14.155)
Contribution of rainfall ($\rho-\rho^*$)	0.002	0.001	0.000	0.001	0.009	0.000
% Decrease [$((\rho-\rho^*)/\rho)*100$]	0.66	0.23	-0.10	0.20	3.17	-0.22
Controlling for standard deviation of rainfall						
Neighborhood Correlation (ρ^*)	0.359*** (19.726)	0.386*** (13.284)	0.214*** (11.700)	0.266*** (20.367)	0.296*** (12.899)	0.196*** (14.043)
Contribution of rainfall SD ($\rho-\rho^*$)	0.004	-0.001	0.004	0.001	0.003	0.003
% Decrease [$((\rho-\rho^*)/\rho)*100$]	1.12	-0.38	1.75	0.20	0.97	1.51
Controlling for monsoon rainfall coefficient of variation						
Neighborhood Correlation (ρ^*)	0.363*** (19.901)	0.379*** (13.135)	0.209*** (11.578)	0.260*** (20.146)	0.299*** (12.975)	0.188*** (13.776)
Contribution of rainfall COV ($\rho-\rho^*$)	0.000	0.005	0.009	0.006	0.000	0.011
% Decrease [$((\rho-\rho^*)/\rho)*100$]	-0.05	1.39	3.91	2.26	-0.08	5.60
Controlling for Agro-ecological zones						
Neighborhood Correlation (ρ^*)	0.316*** (17.834)	0.354*** (11.953)	0.191*** (10.764)	0.237*** (18.965)	0.278*** (12.024)	0.164*** (12.732)
Contribution of Agro-eco zones ($\rho-\rho^*$)	0.046	0.031	0.027	0.029	0.020	0.034
% Decrease [$((\rho-\rho^*)/\rho)*100$]	12.75	7.96	12.20	11.06	6.74	17.32
Controlling for Agro-ecological zones and monsoon rain COV						
Neighborhood Correlation (ρ^*)	0.316*** (17.830)	0.350*** (11.828)	0.192*** (10.761)	0.236*** (18.905)	0.279*** (12.020)	0.162*** (12.615)
Contribution of all geo-climate ($\rho-\rho^*$)	0.046	0.035	0.026	0.031	0.019	0.037
% Decrease [$((\rho-\rho^*)/\rho)*100$]	12.74	9.09	11.87	11.48	6.39	18.79

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Spatial Disparity and Access to Infrastructure and Services

	2000			2010		
	All	Urban	Rural	All	Urban	Rural
Panel A (base case)						
Neighborhood Correlation (ρ)	0.363*** (19.929)	0.385*** (13.271)	0.218*** (11.820)	0.266*** (20.405)	0.298*** (12.998)	0.199*** (14.158)
Panel B (access to electricity)						
Neighborhood Correlation (ρ^*)	0.231*** (14.937)	0.277*** (10.355)	0.154*** (10.100)	0.199*** (17.676)	0.223*** (11.138)	0.161*** (12.858)
Contribution of electricity ($\rho-\rho^*$)	0.131	0.108	0.064	0.068	0.076	0.038
% Decrease [$((\rho-\rho^*)/\rho)*100$]	36.2	28.0	29.2	25.4	25.3	19.2
Panel C (access to phone)						
Neighborhood Correlation (ρ^*)	0.246*** (15.631)	0.246*** (9.702)	0.196*** (11.229)	0.175*** (16.673)	0.164*** (9.704)	0.153*** (12.581)
Contribution of phone ($\rho-\rho^*$)	0.117	0.139	0.022	0.092	0.134	0.046
% Decrease [$((\rho-\rho^*)/\rho)*100$]	32.1	36.1	10.1	34.5	44.9	23.1
Panel D (access to large markets)						
Neighborhood Correlation (ρ^*)	0.318*** (18.170)	0.369*** (12.785)	0.202*** (11.399)	0.237*** (19.190)	0.266*** (12.161)	0.187*** (13.735)
Contribution of access to market ($\rho-\rho^*$)	0.045	0.016	0.015	0.030	0.033	0.012
% Decrease [$((\rho-\rho^*)/\rho)*100$]	12.4	4.2	7.1	11.2	11.0	6.2
Panel E (access to sanitation)						
Neighborhood Correlation (ρ^*)	0.235*** (15.183)	0.269*** (10.159)	0.184*** (10.860)	0.208*** (18.011)	0.205*** (10.632)	0.182*** (13.531)
Contribution of sanitation ($\rho-\rho^*$)	0.128	0.116	0.034	0.058	0.094	0.017
% Decrease [$((\rho-\rho^*)/\rho)*100$]	35.2	30.1	15.4	21.9	31.4	8.6
Panel F (access to clean drinking water)						
Neighborhood Correlation (ρ^*)	0.260*** (16.263)	0.277*** (10.500)	0.218*** (11.777)	0.227*** (18.790)	0.255*** (11.879)	0.193*** (13.932)
Contribution of drink. water ($\rho-\rho^*$)	0.102	0.108	0.000	0.040	0.043	0.006
% Decrease [$((\rho-\rho^*)/\rho)*100$]	28.2	28.1	0.0	14.9	14.5	2.9
Panel G (Infrastructure)						
Neighborhood Correlation (ρ^*)	0.150*** (12.289)	0.111*** (6.128)	0.144*** (9.664)	0.156*** (15.760)	0.130*** (8.608)	0.142*** (12.055)
Contribution of infrastructure ($\rho-\rho^*$)	0.213	0.273	0.073	0.111	0.168	0.057
% Decrease [$((\rho-\rho^*)/\rho)*100$]	58.6	71.0	33.7	41.5	56.3	28.7
Panel H (Infrastructure and geo-climate)						
Neighborhood Correlation (ρ^*)	0.141*** (11.663)	0.100*** (5.493)	0.130*** (8.871)	0.133*** (14.500)	0.118*** (7.863)	0.108*** (10.421)
Cont. of infrastructure & geo-climate ($\rho-\rho^*$)	0.222	0.285	0.088	0.133	0.181	0.091
% Decrease [$((\rho-\rho^*)/\rho)*100$]	61.1	74.0	40.4	50.0	60.6	45.8

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Spatial Disparity and Sorting of household Attributes

	2000			2010		
	All	Urban	Rural	All	Urban	Rural
Base Case	Panel A (base case)					
Neighborhood Correlation (ρ)	0.363*** (19.929)	0.385*** (13.271)	0.218*** (11.820)	0.266*** (20.405)	0.298*** (12.998)	0.199*** (14.158)
	Panel B (Education)					
Neighborhood Correlation (ρ^*)	0.192*** (13.812)	0.185*** (8.201)	0.180*** (10.819)	0.160*** (16.060)	0.119*** (8.423)	0.174*** (13.316)
Contribution of education ($\rho - \rho^*$)	0.171	0.200	0.037	0.106	0.179	0.025
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	47.2	51.9	17.2	39.8	60.1	12.5
	Panel C (Skill composition)					
Neighborhood Correlation (ρ^*)	0.313*** (17.881)	0.349*** (12.220)	0.209*** (11.560)	0.219*** (18.478)	0.222*** (11.111)	0.199*** (14.117)
Contribution of skill comp. ($\rho - \rho^*$)	0.050	0.036	0.008	0.047	0.076	0.000
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	13.7	9.4	3.8	17.8	25.4	0.1
	Panel D (Sectoral composition)					
Neighborhood Correlation (ρ^*)	0.318*** (18.082)	0.384*** (13.163)	0.207*** (11.508)	0.227*** (18.790)	0.253*** (11.838)	0.191*** (13.876)
Cont. of sectoral comp. ($\rho - \rho^*$)	0.045	0.001	0.010	0.040	0.045	0.008
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	12.3	0.2	4.7	14.9	15.2	3.8
	Panel E (Education, Skill and Sectoral composition)					
Neighborhood Correlation (ρ^*)	0.190*** (13.698)	0.185*** (8.173)	0.176*** (10.618)	0.159*** (15.958)	0.120*** (8.370)	0.167*** (13.006)
Cont. of human capital ($\rho - \rho^*$)	0.173	0.200	0.042	0.107	0.179	0.032
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	47.6	51.9	19.2	40.3	59.8	16.1
	Panel F (share of children)					
Neighborhood Correlation (ρ^*)	0.295*** (17.396)	0.305*** (11.135)	0.203*** (11.415)	0.246*** (19.581)	0.271*** (12.306)	0.192*** (13.912)
Cont. of dependency ($\rho - \rho^*$)	0.067	0.080	0.015	0.020	0.027	0.007
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	18.6	20.8	6.8	7.5	9.1	3.5
	Panel G (Education, Skill and Sectoral composition, dependency)					
Neighborhood Correlation (ρ^*)	0.179*** (13.352)	0.166*** (7.682)	0.171*** (10.461)	0.159*** (15.937)	0.118*** (8.284)	0.167*** (12.992)
Cont. of all household sorting ($\rho - \rho^*$)	0.183	0.219	0.047	0.107	0.181	0.032
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	50.6	56.9	21.5	40.3	60.6	16.1
	Panel H (All sorting plus geography)					
Neighborhood Correlation (ρ^*)	0.152*** (12.005)	0.136*** (6.510)	0.140*** (9.225)	0.128*** (14.284)	0.099*** (7.325)	0.131*** (11.398)
Cont. of sorting & geo -climate ($\rho - \rho^*$)	0.211	0.249	0.078	0.138	0.200	0.068
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	58.1	64.8	35.6	51.9	66.9	34.3

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Spatial Disparity and Sorting of household Attributes

	2000			2010		
	All	Urban	Rural	All	Urban	Rural
Base Case	Panel A (base case)					
Neighborhood Correlation (ρ)	0.363*** (19.929)	0.385*** (13.271)	0.218*** (11.820)	0.266*** (20.405)	0.298*** (12.998)	0.199*** (14.158)
	Panel B (Education)					
Neighborhood Correlation (ρ^*)	0.192*** (13.812)	0.185*** (8.201)	0.180*** (10.819)	0.160*** (16.060)	0.119*** (8.423)	0.174*** (13.316)
Contribution of education ($\rho - \rho^*$)	0.171	0.200	0.037	0.106	0.179	0.025
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	47.2	51.9	17.2	39.8	60.1	12.5
	Panel C (Skill composition)					
Neighborhood Correlation (ρ^*)	0.313*** (17.881)	0.349*** (12.220)	0.209*** (11.560)	0.219*** (18.478)	0.222*** (11.111)	0.199*** (14.117)
Contribution of skill comp. ($\rho - \rho^*$)	0.050	0.036	0.008	0.047	0.076	0.000
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	13.7	9.4	3.8	17.8	25.4	0.1
	Panel D (Sectoral composition)					
Neighborhood Correlation (ρ^*)	0.318*** (18.082)	0.384*** (13.163)	0.207*** (11.508)	0.227*** (18.790)	0.253*** (11.838)	0.191*** (13.876)
Cont. of sectoral comp. ($\rho - \rho^*$)	0.045	0.001	0.010	0.040	0.045	0.008
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	12.3	0.2	4.7	14.9	15.2	3.8
	Panel E (Education, Skill and Sectoral composition)					
Neighborhood Correlation (ρ^*)	0.190*** (13.698)	0.185*** (8.173)	0.176*** (10.618)	0.159*** (15.958)	0.120*** (8.370)	0.167*** (13.006)
Cont. of human capital ($\rho - \rho^*$)	0.173	0.200	0.042	0.107	0.179	0.032
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	47.6	51.9	19.2	40.3	59.8	16.1
	Panel F (share of children)					
Neighborhood Correlation (ρ^*)	0.295*** (17.396)	0.305*** (11.135)	0.203*** (11.415)	0.246*** (19.581)	0.271*** (12.306)	0.192*** (13.912)
Cont. of dependency ($\rho - \rho^*$)	0.067	0.080	0.015	0.020	0.027	0.007
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	18.6	20.8	6.8	7.5	9.1	3.5
	Panel G (Education, Skill and Sectoral composition, dependency)					
Neighborhood Correlation (ρ^*)	0.179*** (13.352)	0.166*** (7.682)	0.171*** (10.461)	0.159*** (15.937)	0.118*** (8.284)	0.167*** (12.992)
Cont. of all household sorting ($\rho - \rho^*$)	0.183	0.219	0.047	0.107	0.181	0.032
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	50.6	56.9	21.5	40.3	60.6	16.1
	Panel H (All sorting plus geography)					
Neighborhood Correlation (ρ^*)	0.152*** (12.005)	0.136*** (6.510)	0.140*** (9.225)	0.128*** (14.284)	0.099*** (7.325)	0.131*** (11.398)
Cont. of sorting & geo -climate ($\rho - \rho^*$)	0.211	0.249	0.078	0.138	0.200	0.068
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	58.1	64.8	35.6	51.9	66.9	34.3

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Spatial Disparity, Access to Infrastructure and Sorting of household Attributes

	2000			2010		
	All	Urban	Rural	All	Urban	Rural
Base Case	Panel A (base case)					
Neighborhood Correlation (ρ)	0.363*** (19.929)	0.385*** (13.271)	0.218*** (11.820)	0.266*** (20.405)	0.298*** (12.998)	0.199*** (14.158)
	Panel B (Sorting, access to infrastructure)					
Neighborhood Correlation (ρ^*)	0.115*** (10.832)	0.057*** (3.974)	0.127*** (9.025)	0.124*** (14.223)	0.081*** (6.842)	0.132*** (11.623)
Cont. of sorting & infrastructure ($\rho - \rho^*$)	0.248	0.328	0.091	0.142	0.218	0.067
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	68.3	85.3	41.7	53.3	72.9	33.4
	Panel C (Sorting, infrastructure & geo-climate)					
Neighborhood Correlation (ρ^*)	0.106*** (10.136)	0.050*** (3.440)	0.112*** (8.194)	0.102*** (12.823)	0.074*** (6.228)	0.099*** (9.961)
Cont. of sorting, infra., geo-clim. ($\rho - \rho^*$)	0.257	0.335	0.106	0.164	0.225	0.100
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	70.9	87.0	48.6	61.7	75.3	50.1
	Panel D (Sorting, infrastructure, geo-climate & prices)					
Neighborhood Correlation (ρ^*)	0.092*** (9.388)	0.043*** (3.075)	0.090*** (7.351)	0.099*** (12.591)	0.073*** (6.162)	0.094*** (9.687)
Cont. of all plus prices ($\rho - \rho^*$)	0.271	0.341	0.128	0.168	0.225	0.105
% Decrease [$((\rho - \rho^*)/\rho) * 100$]	74.6	88.7	58.7	63.0	75.5	52.6

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Spatial Disparity, Access to Infrastructure and Sorting of household Attributes
Regression Coefficients

	2000			2010		
	All	Urban	Rural	All	Urban	Rural
Years of Education	0.052*** (7.700)	0.051*** (6.085)	0.048*** (4.486)	0.070*** (6.609)	0.120*** (6.634)	0.026* (1.957)
% of workers skilled	-0.037 (-0.330)	-0.021 (-0.170)	-0.345 (-1.453)	0.136 (1.301)	-0.074 (-0.489)	-0.149 (-0.941)
% of workers semi-skilled	-0.040 (-0.443)	-0.004 (-0.038)	-0.211 (-1.402)	-0.114 (-1.415)	0.042 (0.373)	-0.213* (-1.761)
% of workers in manufacturing	-0.076 (-0.720)	-0.156 (-1.030)	0.278* (1.666)	-0.275*** (-3.021)	-0.353** (-2.432)	-0.155 (-1.197)
% of workers in services	-0.181** (-2.270)	-0.335*** (-2.847)	0.132 (1.088)	-0.113 (-1.610)	-0.164 (-1.463)	0.049 (0.470)
% children	-0.637*** (-4.364)	-0.502** (-2.453)	-0.655*** (-3.277)	-0.119 (-0.788)	0.416 (1.403)	-0.330* (-1.930)
% of household with phone	0.911*** (6.933)	0.925*** (6.973)	2.045*** (2.819)	0.218*** (3.466)	0.364*** (2.583)	0.204*** (2.874)
% household with electricity	0.223*** (4.983)	0.339*** (4.296)	0.306*** (5.010)	0.138*** (3.699)	0.197** (1.977)	0.204*** (4.940)
% of hh with sanitary latrine	0.088 (1.578)	0.059 (0.710)	-0.114 (-1.250)	0.084 (1.539)	0.059 (0.576)	-0.006 (-0.086)
% with water seal latrine	0.086 (0.939)	0.149 (1.332)	-0.008 (-0.030)	0.092 (1.636)	0.009 (0.088)	0.154** (2.160)
% with paved pit latrine	-0.045 (-0.742)	-0.065 (-0.754)	0.042 (0.441)	0.042 (0.786)	-0.014 (-0.136)	0.055 (0.866)
% unpaved permanent latrine	0.062 (1.286)	-0.143 (-1.597)	0.098* (1.675)	-0.048 (-0.982)	-0.185* (-1.655)	0.056 (1.061)
% using tap water	-0.000 (-0.004)	-0.097 (-0.330)	-0.211 (-0.891)	-0.013 (-0.194)	0.017 (0.146)	0.050 (0.349)
% using tubewell water	-0.111 (-1.138)	-0.278 (-0.970)	-0.067 (-0.670)	-0.068 (-1.229)	-0.000 (-0.001)	-0.064 (-0.983)
Log(distance to large cities)	0.041** (2.286)	0.018 (0.665)	0.111*** (3.321)	-0.051** (-2.569)	-0.045* (-1.738)	-0.027 (-0.821)
Rain Standard Deviation	0.000 (1.352)	0.000 (0.134)	-0.000 (-1.166)	0.000 (1.472)	0.000 (0.938)	0.000 (0.888)
Monsoon Rain Coeff. Of variation	-1.545* (-1.947)	-1.373 (-0.825)	1.287 (1.242)	-2.010*** (-3.248)	-1.485 (-1.623)	-2.019** (-2.352)
Rice price index	0.038*** (4.686)	0.039*** (2.757)	0.045*** (4.728)	0.005 (1.643)	0.004 (0.858)	0.009** (2.290)
log(housing cost)	0.213** (2.213)	-0.034 (-0.185)	0.572*** (3.486)	0.160* (1.958)	0.222 (1.632)	0.110 (1.093)
Non-traded price index	0.002** (2.471)	0.002 (1.561)	0.001 (1.020)	0.001*** (2.950)	0.000 (0.339)	0.002*** (2.728)

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Sources of spatial convergence or divergence

	Urban			Rural			Pooled		
	2000	2010	Change ($\rho_{2000}-\rho_{2010}$)	2000	2010	Change ($\rho_{2000}-\rho_{2010}$)	2000	2010	Change ($\rho_{2000}-\rho_{2010}$)
Base: ρ	0.385	0.298	0.086	0.218	0.199	0.019	0.363	0.266	0.096
Unexplained by Correlates(υ)	0.050	0.074	-0.030	0.112	0.099	-0.004	0.106	0.102	-0.007
Upper bound									
Infrastructure: ρ_1	0.285	0.181	0.104	0.088	0.091	-0.003	0.222	0.133	0.088
% of base	74.01	60.62	120.23	40.38	45.81	-17.33	61.09	49.99	91.81
Sorting: ρ_2	0.219	0.181	0.038	0.047	0.032	0.015	0.183	0.107	0.076
% of base	56.93	60.61	44.22	21.54	16.09	79.44	50.55	40.34	78.80
Lower bound									
Infrastructure: $\rho-\rho_2-\upsilon$	0.116	0.044	0.078	0.059	0.068	0.008	0.074	0.057	0.027
% of base	30.11	14.73	90.24	27.10	33.98	43.79	20.31	21.31	27.98
Sorting: $\rho-\rho_1-\upsilon$	0.050	0.044	0.012	0.018	0.008	0.026	0.035	0.031	0.014
% of base	13.03	14.71	14.22	8.26	4.26	140.57	9.77	11.66	14.97

Table A.1: Summary Statistics

	National		Urban		Rural	
	Mean	SD	Mean	SD	Mean	SD
	2010					
Real Per Capita Expenditure (taka)	1254.8	973.6	1454.6	1205.3	1142.7	793.5
Average years of education	3.547	1.455	4.534	1.593	2.994	1.014
Prop. In skilled job	0.108	0.117	0.173	0.146	0.071	0.074
Prop. In semi-skilled job	0.344	0.195	0.452	0.189	0.283	0.170
Prop. In manufacturing	0.164	0.154	0.228	0.177	0.129	0.125
Prop. In services	0.445	0.235	0.621	0.212	0.346	0.184
Prop. of household with phone	0.652	0.209	0.790	0.159	0.574	0.193
Prop. of household with electricity	0.576	0.340	0.844	0.203	0.426	0.307
sanitary latrine	0.198	0.249	0.290	0.288	0.146	0.207
pacca(water seal) latrine	0.172	0.195	0.243	0.222	0.133	0.164
pacca(pit) latrine	0.157	0.196	0.160	0.184	0.156	0.202
katcha(perm) latrine	0.240	0.233	0.186	0.216	0.270	0.237
supply	0.080	0.222	0.197	0.326	0.014	0.070
Tubewell	0.884	0.259	0.773	0.343	0.947	0.167
Distance to large cities	331.773	158.545	302.742	168.268	348.066	150.394
Monsoon Rain COV	0.181	0.026	0.180	0.025	0.182	0.027
Rice Price	44.465	2.834	45.745	2.977	43.746	2.476
Non-traded Price	71.244	22.006	73.499	22.743	69.978	21.480
Housing Value Index	1589794	295172	1619459	300214	1573145	291002
	2000					
Real Per Capita Expenditure (taka)	868.043	771.171	1098.000	1150.917	758.540	458.417
Average years of education	3.431	2.257	5.133	2.752	2.620	1.369
Prop. In skilled job	0.077	0.103	0.127	0.149	0.053	0.058
Prop. In semi-skilled job	0.283	0.206	0.461	0.201	0.197	0.145
Prop. In manufacturing	0.112	0.134	0.182	0.161	0.078	0.104
Prop. In services	0.369	0.231	0.580	0.221	0.268	0.155
Prop. of household with phone	0.021	0.074	0.059	0.120	0.003	0.017
Prop. of household with electricity	0.373	0.364	0.765	0.272	0.187	0.229
sanitary latrine	0.173	0.240	0.323	0.314	0.102	0.150
pacca(water seal) latrine	0.057	0.114	0.130	0.168	0.022	0.044
pacca(pit) latrine	0.126	0.187	0.206	0.248	0.088	0.134
katcha(perm) latrine	0.208	0.212	0.146	0.198	0.237	0.212
supply	0.088	0.253	0.264	0.384	0.004	0.051
Tubewell	0.881	0.263	0.725	0.381	0.956	0.128
Distance to large cities	308.0	171.6	229.6	184.0	345.3	151.8
Monsoon Rain COV	0.183	0.026	0.180	0.026	0.184	0.026
Rice Price	19.295	1.506	20.225	1.437	18.852	1.326
Non-traded Price	50.338	16.237	52.438	14.702	49.329	16.833
Housing Value Index	435477	87674	470015	132296	419031	46654

Table A.2: Spatial Disparity, Access to Infrastructure and Sorting of household Attributes
Regression Coefficients from separate regressions (each panel reports result from one regression)

	2000			2010		
	All	Urban	Rural	All	Urban	Rural
Mean Rainfall	-0.000** (-2.276)	-0.000 (-1.285)	-0.000 (-0.851)	0.000 (1.572)	0.000*** (3.176)	0.000 (0.345)
Rain Standard Deviation	-0.001*** (-2.763)	0.000 (0.288)	-0.000** (-2.414)	-0.000 (-1.581)	0.001* (1.933)	-0.000*** (-2.686)
Monsoon Rain Coeff. Of variation	-0.431 (-0.683)	2.593** (2.340)	-1.948*** (-3.461)	-1.830*** (-4.220)	-0.768 (-0.867)	-2.107*** (-4.981)
% household with electricity	0.577*** (17.705)	0.862*** (9.811)	0.557*** (10.230)	0.443*** (15.405)	0.877*** (9.548)	0.329*** (9.650)
Access to sanitation						
% of hh with sanitary latrine	0.702*** (13.364)	0.865*** (8.226)	0.459*** (5.084)	0.548*** (11.192)	0.715*** (6.592)	0.253*** (4.238)
% with water seal latrine	1.028*** (10.593)	1.141*** (7.605)	0.960*** (3.102)	0.463*** (7.994)	0.509*** (4.269)	0.339*** (4.691)
% with paved pit latrine	0.365*** (5.760)	0.510*** (4.461)	0.276*** (2.710)	0.165*** (2.886)	0.071 (0.553)	0.213*** (3.560)
% unpaved permanent latrine	0.153** (2.439)	0.177 (1.279)	0.210*** (3.274)	0.112** (1.992)	0.026 (0.189)	0.144** (2.555)
Access to drinking water						
% using tap water	0.777*** (5.541)	0.928* (1.931)	0.403 (1.290)	0.587*** (6.879)	0.626*** (3.886)	0.602*** (3.319)
% using tubewell water	0.100 (0.727)	0.345 (0.713)	0.001 (0.006)	0.059 (0.802)	0.213 (1.390)	-0.011 (-0.140)
% of household with phone	2.511*** (16.438)	2.124*** (11.724)	4.631*** (5.550)	0.825*** (18.844)	1.434*** (14.274)	0.570*** (10.751)
Access to large urban markets	-0.131*** (-9.273)	-0.079*** (-3.536)	-0.116*** (-4.639)	-0.154*** (-9.566)	-0.145*** (-5.901)	-0.114*** (-5.253)
Average years of education	0.104*** (21.879)	0.108*** (15.454)	0.073*** (7.415)	0.126*** (20.916)	0.161*** (18.528)	0.081*** (7.571)
Skill composition of workers						
% of workers skilled	1.141*** (8.936)	0.735*** (3.946)	0.673*** (2.706)	1.076*** (12.220)	1.281*** (9.339)	0.236 (1.506)
% of workers semi-skilled	0.257*** (3.757)	-0.289** (-2.066)	0.214** (2.143)	0.136** (2.573)	0.143 (1.346)	0.031 (0.445)
Sectoral composition						
% of workers in manufacturing	0.408*** (3.889)	0.059 (0.276)	0.297** (2.134)	0.175** (2.565)	0.481*** (3.632)	-0.065 (-0.712)
% of workers in services	0.519*** (8.440)	0.220 (1.411)	0.299*** (3.207)	0.493*** (11.042)	0.788*** (7.119)	0.259*** (4.153)

Robust z statistics in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%