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Examining the Impact of Climate Change on Migration through the Agricultural Channel:

Evidence from District Level Panel Data from Bangladesh

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Contents

Abstract

This paper studies how changes in climatic variables such as temperature and rainfall impact migration through agriculture.
We use district level data (64 districts) for 3 inter-census periods (1974-1980, 1981-1990 and 1991-2000) to analyse historical migration related outcomes. We find that fluctuations in temperature and rainfall contributed to a decline in agricultural productivity as measured by revenues from agriculture. Fixed Effect and Instrumental Variable estimations show that about one standard deviation decrease in real per capita agricultural revenue increases the net out-migration rate by 1.4 to 2.4 percent, controlling for unobserved effects for districts and years. Using our estimates and available forecasts in the literature, we predict that the net out-migration rate will be about 22 percent higher in 2030 than in 1990, assuming the variability in temperature stays stable and there are no behavioural responses from the farmers.

Examining the Impact of Climate Change on Migration through the Agricultural Channel: Evidence from District Level Panel Data from Bangladesh

1. Introduction

Bangladesh is recognized as one of the most vulnerable countries to climate change because of its unique geographical location. UNDP identifies Bangladesh as the most vulnerable country to tropical cyclones and the 6th most vulnerable country to floods. It is estimated that a 0.5 degree Celsius rise in mean temperature and 10-cm rise in sea level could lead to an inundation of 15 percent (approximately 750 km^2) of the Sundarban forests, the largest mangrove ecosystem in Asia (IPCC, 2001). A World Bank study (2000) projects that by the year 2050, average temperature will increase by 1.8 degree Celsius and precipitation will fluctuate 37 percent compared to 1990 in the dry season and sea level will rise by 50 cm in Bangladesh.

These climate-change-induced meteorological conditions and related natural disasters have direct bearing on the livelihood of the people. Among others, migration, both internal and international, is one of the most frequently used coping strategies affected people adopt to mitigate income shocks. This study systematically investigates the impact of climate change on migration. We are particularly interested to study how the impact works through agriculture. Using district level data (64 districts) for 3 inter-census periods (1974-1980, 1981-1990 and 1991-2000), we study the impact of changes in climatic variables on the migration rate through agricultural channel.

Changes in climatic variables impact agriculture more than any other sectors such as service or manufacturing, for the former is more weather dependent than the latter, especially in developing countries. It is well established in the literature that changes in climatic variables such as atmospheric carbon dioxide concentration, rainfall, humidity, temperature, etc. affect agricultural output. Models of cereal crops indicate that potential yields are projected to decrease for most projected increases in temperature changes in most tropical and subtropical regions (IPCC, 2001).

Developing countries are, arguably, disproportionately affected by climate change relative to developed countries. While climate change caused by the doubling of carbon dioxide concentration lowers global crop production by a little, the effect is much larger for developing countries (Rosenzweig and Parry, 1994). Nelson et al. (2009) also found similar results for developing countries and further noted that South Asia would be particularly hard hit. Studies on Bangladesh also corroborate the above findings. About 3-4 million hectors of land are estimated to be affected by drought and in some Barind areas (North western part of Bangladesh) crop loss due to drought is estimated to be as high as 70-90 percent (Rashid and Islam, 2007). Aman, which is a rain fed crop, is affected most.

Though the nexus between climate change and agriculture is well established, their links with migration are rather weak. The literature mostly uses natural disasters as a proxy for climate change in determining the impact of climate change on migration, though such disasters may or may not be related to climate change. Using an agent based model, Hassani-Mahmooe and Parris (2012) predict significant out-migration in drought prone western and flood and cyclone prone southern areas in Bangladesh. Their model predicts that the size of internal migrants in Bangladesh will be between 3 and 10 million over the next 40 years. Studies on Africa focus mostly on the impact of drought on migration. Findley (1994) studied migration in rural Mali during the 1983-85 droughts and found that droughts led to higher short distance migration but lower long distance ones because the people could not afford the latter. Meze-Hausken (2000) analysed drought-induced migration and the adaptation capacity of subsistence farmers in Northern Ethiopia.

There has been no rigorous study on the long run impact of the changes in climatic variables on migration until Feng et al. (2010). Using state-level data from Mexico for the period 1995-2005, they found a significant effect of climate-driven changes in crop yields on the rate of emigration to the United States. Using the estimated sensitivity of migration to climate change they also project emigration responses to future climate change scenarios. The same authors, Feng et al. (2012) also studied the link between agricultural productivity and net migration in the United States using a county-level panel for the period of 1970-2009. This study found that a 1 percent decrease in yields led to a 0.17 percent net reduction of the population through migration.

From methodological point of view, this study follows Feng et al. (2010) closely, but differs from it in three major ways. First, we use a more appropriate measure of agricultural productivity to study migration response. Households' decision to migrate depends on income, not on physical quantity. A bad harvest may be associated with higher price and thus higher income. Therefore, unlike Feng et al. (2010) who used output per acre, we use per capita agricultural revenue. Moreover, a district with high agricultural productivity may also be a district with large population. So, per capita agricultural revenue is more appropriate than revenue per unit of area (e.g., acre). Secondly, Feng et al. (2010) did not control for temporal unobserved effects which may confound the results. We recognize the significance of unobserved effects in establishing causal inference and sequentially introduce partial to full temporal and spatial unobserved effects. Thirdly, we control for natural disaster as disaster may be correlated with climate variables. Hence, it may cause omitted variable bias if dropped from the model.

We compile a unique data set on migration, agricultural productivity and weather variables at the district level for three inter-census periods – 1974-80, 1981-90 and 1991-2000. Since migration data is not readily available, we estimate it from population censuses. We exclude two urban districts – Dhaka and Chittagong and three tribal hilly districts – Bandarban, Khagrachhari and Rangamati where planned settlement of Bengali people occurred. We run both FE and IV methods to estimate the impact and control for temporal and spatial unobserved effects. The weather variables are used as instruments for agricultural productivity.

The fixed effect results show that about one standard deviation decrease in per capita real agricultural revenue leads net out-migration to increase by 1.0 to 1.4 percent. With the set of weather variables as instruments, the fixed effect with IV results show that one standard deviation decrease in per capita real agricultural revenue results in 2.0 to 2.4 percent increases in net out-migration.

Using the marginal impacts, we also calculate the elasticities of net out-migration with respect to weather variables at the mean values. The calculation shows that a 1 percent increase in standard deviation of rainfall and a 1 percent increase in standard deviation of minimum temperature in the wet season result in about 0.81 percent and 3 percent increase in net out-migration rate respectively. We also perform some forecast exercises based on future predictions of rainfall and temperature variability. If we assume no temperature variability in the future, the rate of net out-migration will increase by 22 percent in 2030 compared to the rate in 1990. However, if we account for the decreasing temperature variability in the future, as predicted by a recent study, then in-migration dominates out-migration. The prediction then is that the in-migration rate will increase by 10 percent in the year 2030 compared to 1990.

The rest of the paper is organized as follows. The section 2 provides a conceptual note; section 3 describes data, variables and descriptive statistics; section 4 lays out the empirical strategies; section 5 describes regression results and discusses some relevant elasticities and forecasts and finally section 6 draws conclusion.

2. Conceptual Note

A typical rural household in a developing country lives mostly on natural resources (e.g., land, water) which are vulnerable to climate change induced shocks. Change of climatic variables such as temperature, rainfall, sun shine, humidity, etc. disrupts access of the household to these resources (e.g., submerging of agricultural land, flooding of water bodies). Even if the household has access to these resources, the return from these resources may fall drastically (e.g., extreme weather, salinity of water, sedimentation). Hence, climate change can affect households directly by affecting their occupations (e.g., a fisherman has to leave his job and his place because the water bodies have dried up) or indirectly through affecting agriculture (e.g., lower revenue and wage due to lower productivity).

Note that in a developing country non-farm opportunities are very low and are highly correlated with agriculture. Non-farm activities which depend heavily on agriculture such as agri-business, food processing, etc. also bear the brunt of the change in climatic conditions. Even some non-farm activities which are uncorrelated with agriculture may be adversely affected. For example, rickshaw or van pulling in rural areas in Bangladesh is largely affected when the roads are submerged by floods. In short, in the face of climate change people involved in agriculture find it very difficult to switch their jobs to other non-farm sectors in their locality.

A developing country is typically characterized by underdeveloped credit and insurance markets. In the absence of well-functioning credit or insurance markets, households depend on non-market solutions in order to spread the risk by diversifying their income portfolio. The affected people use a host of coping strategies, both formal and informal; some are individual or household based and some are group based (Skoufias, 2003). Sale of assets, loan from money lender, child labour, reduced food consumption and migration are the main used individual or household based informal strategies, while rotating credit and saving associations and networks are the group based solutions. The formal non-market based strategies involve relying on public safety net programs. It is important to note that changes in climate variables are largely aggregate shocks which affect a region or part of a region. This implies that group based informal mechanisms become less effective which in normal circumstances may be quite effective in providing insurance (Morduch, 1999). That is, when a farmer is affected adversely, it is highly likely that other farmers in that region are also affected adversely by the shock. This type of aggregate shocks may also limit the market based strategies. If the rural depositors withdraw a large part of their deposit from rural financial institutions in the face of climate-change induced crop failure, these institutions can no longer be effective in providing credit to mitigate risks (Binswanger and Rosenzweig, 1986).

In developing countries resource constrained governments have limitations in delivering public goods in mitigating climate change related shocks. It is argued that the safety net programs in developing countries are inadequate and sometimes wrongly targeted. Therefore, in the absence of market based solutions, and due to ineffective group based mechanisms and inadequate public supports, migration may become a dominant strategy for the households to cope with the shocks (Stark and Levhari, 1982; Stark,1991). Households look for another place which is uncorrelated or negatively correlated with the shocks of the place of origin and decide to send one of the members for temporary work or to migrate permanently. This decision also depends on the availability of other complementary inputs such as information, networks, etc.

Initially migration decision was seen as the process of development where wage differential between places was argued to be the key motivation for migration. (Lewis,1954; Ranis and Fei, 1961; Harris and Todaro, 1970). Potential migrants estimate the costs and benefits of moving to alternative locations and migrate to where the expected discounted net returns are the greatest. However, this decision may not necessarily be an isolated individual decision, rather an outcome of intra-household decision making, be it individual or family migration. (Stark and Levhari, 1982; Stark, 1984; Stark and Bloom, 1985; Stark, 1991). Therefore, there exists a cooperative equilibrium in the household regarding migration decisions and the contract becomes self-fulfilling in the absence of functioning credit and insurance markets.

3. Data, Variables and Descriptive Statistics

Agriculture

This study considers six major crops defined by the Agriculture Wing, Bangladesh Bureau of Statistics (BBS). These are three varieties of rice (Aus, Aman, Boro), jute, wheat and potato. The sources of agriculture data used are: i) Yearbook of Agricultural Statistics, BBS, ii) Agriculture Census Report, BBS, and iii) Thana Statistics and Upazila Statistics, BBS[1].

[1] The Yearbook reports agricultural data at regional level, not at the district level. There are 23 agricultural regions defined by BBS and each region is composed of one or more current administrative districts. Agriculture Censuses in Bangladesh were conducted in 1977-78, 1986-87, 1996 and 2008. These censuses report agricultural data at the Thana and district level only in the census years. Thana Statistics and Upazila Statistics report agriculture data for the period from 1974 to 1984 only. Note that sub-divisions are made up of several Thanas and sub-divisions were later turned into new districts in the year 1984.

We use Thana Statistics and Upazila Statistics to create district-wise data for the period 1974-75 to 1982-83. For the other periods 1983-84 to 2000-01, data is available at the regional level. So, we divide the regional output data into districts using the data of three censuses - 1986-87, 1996 and 2008. By interpolating the data on cultivated land of 1982-83 (Upazila Statistics) and 1986-87 (Census), and then dividing the regional output according to a district's share in cultivable land, we fill in the output data for the years 1983-1985. Then again we interpolate the cultivable land at the district level for the period 1987-2000 using last three census years and distribute the output accordingly. BBS also publishes whole sale price of selected crops in each year. Note that the price data does not vary across districts or regions.

Our variable of interest is per capita real revenue from agricultural output[2]. At the aggregate level, real revenue per capita increased from 1974-80 to 1981-90 but decreased afterwards (Table 1). District level disaggregates also show this pattern for a large number of districts. (Table A3). The reason for this declining trend in the last period is largely due to the fact that increases in CPI and population offset the increase in nominal agricultural revenue.

Disaster

We consider flood, cyclone and drought as these are directly related to climate change. We collect data on damaged cropped area at the Thana level from Thana Statistics and Upazila Statistics for the periods 1974-75 to 1982-83. We then sum them up to create district wise data. For the periods 1983-2000, we follow the same method as we have used to create output for the districts.

We use the ratio of damaged cropped area (due to disaster) to total cropped area to capture the extent of damage. Descriptive statistics shows that the share of damaged cropped area in total cropped area has increased over time (Table 1).

Weather

We collect monthly average rainfall, monthly average maximum and minimum temperature for the period 1974-2000 from Bangladesh Agricultural Research Council (BARC). There are 32 weather stations in Bangladesh and they cover 64 districts. That is, weather data varies only across weather stations. So, the challenge is to assign weather stations to each district. We use the average of nearest ones where there is no weather station in a district. In some cases a district has multiple weather stations and we use simple average of all.

The weather variables include mean and standard deviations of temperature (maximum and minimum) and rainfall. Since crops follow seasonal calendar and weather varies significantly between seasons, we split a calendar year into two seasons – dry (Oct- March) and wet (April-Sept). All weather variables are, thus, for two seasons.

Note that in case of temperature, data on monthly maximum and monthly minimum are available. So, we create seasonal average of maximum and minimum temperature. Not only the average but also the fluctuation of temperature in each season might have impact on agricultural productivity. Hence, we use two types of standard deviations of temperature- standard deviation over months and the standard deviation over census years. In the first case, for an example, we take standard deviations of maximum temperature of the months from October to March (dry season) and then take average over census periods. Hereafter, we will refer this standard deviation as SD1. In the second case, we take average of maximum temperature of the months of dry season and then take standard deviation over census periods. Hereafter, we will refer this standard deviation as SD2.

Average monthly rainfall data is available. So, we create seasonal average rainfall for dry and wet seasons. We create two types of standard deviations, as described above, for rainfall as well.

Table 1 shows that average rainfall in dry season has increased from 56 cm in 1974-80 to 66 cm in 1990s. However average rainfall in the wet season has decreased from 333 cm in 1980s to 317 cm in 1990s. Both monthly fluctuation (SD1) and yearly fluctuation (SD2) in rainfall have increased in dry season and decreased in wet season, though SD2 increased in 1980s and then fell in 1990s in dry season.

[2] In order to create per capita real revenue, we first add up revenue from all six crops and then divide it by CPI for that year to get real revenue. We then take the average of inter-census periods and divide it by average inter-census population. Average inter-census population is created by taking average of the population of two adjacent census years.

Though average maximum and minimum temperatures in both seasons have not changed much during the sample period, they tend to fluctuate. These two temperatures experienced more yearly fluctuations (SD2) than the monthly fluctuations (SD1).

District wise variations of SD1 of rainfall and temperature are shown in Figure A1 and A2. Figure A1 shows that within a district monthly fluctuation of rainfall is higher in wet season than the dry season. Figure A2 shows that minimum temperature tends to fluctuate more over months in dry season than the maximum temperature.

Migration

Migration data is not available in any secondary sources. Data on international migration is not available at the district level. Therefore, we estimate the net migration using the method described in the following sub-section.

Estimation of migration rate

We use the indirect method of estimating net migration used by United Nations (1970). The basic idea of this method is that the population increment between any two dates for any given geographic area is the result of natural increase (births – deaths) and net migratory movement. Given the population of an area at two points in time and an estimate of natural increase during the interval, we can calculate the number that would be expected at the end of the interval in the absence of migration. Then net change due to migration equals to the difference between observed and expected numbers of population at the end of the interval. We use probability of survival to estimate the expected population. The net migration is then defined as:

$$M(x) = p_{i,x+n,t+n} - S_x p_{i,x,t} = p_{i,x+n,t+n} - \frac{P_{x+n,t+n}}{P_{x,t}} \; p_{i,x,t}$$

Where, *M(x)* is the net migration of survivors among persons aged *x* at the first census in a given area (they will be aged *x+n* at the second census); $p_{i,x,t}$ is the population in the i^{th} area in a particular age group *x* in the census year *t*; $p_{i,s+n,t+n}$ is the corresponding population *n* years older. That is, *x+n* in the next census year *t+n*; $p_{x,t}$; is the population aged *x* in that area at the first census; $p_{x+n,t+n}$ is the population aged *x+n* years in the same area at the second census separated from the first census by *n* years and *S* is the survival ratio.

We calculate the migration rate between two census periods *t* and *t+10* using the following formula: Migration Rate =

$$\frac{M_{i,t+10}}{(p_t + p_{t+10})/2}$$

In order to implement this method, we require district-wise age specific population data since survival ratios are calculated for each age group. We get data for age-groups (0-4, 5-9, ...65-69, 70+) from the censuses[3]. Table A2 in the appendix describes in details how net migration is calculated for a district (Comilla) between 1991 and 2001. Note that district wise survival ratio is not available. Therefore, the country-wide survival ratio is used for all districts for all age groups.

In Comilla district in 1991 there were 298726 persons in the age group 20-24. After ten years, in 2001, if no one dies or migrates (in or out) the size should remain same for the age group 30-34. However, the actual size of this group was 274740 in 2001. This shrink in the size of this cohort is due to death and migration. However, we calculated that country wide survival ratio of this cohort is 0.992. With this survival ratio, the population in Comilla district was expected to be 296390 in 2001. However, the actual population was much lower than this and this difference is due to migration. That is, net out-migration is 21650. We sum net out-migration over all age groups to get total net out-migration. We divide it by the average population of 1991 and 2001 to get net migration rate.

[3] In 1981 census, BBS collected Thana (lower administrative area) wise age specific data for 19 districts. So, we identify the Thanas under the new 64 districts and create back new district wise population. In 1974 census, BBS did not collect Thana wise population data. It collected sub-division wise age-group specific data. Since the sub-divisions were made new districts, we use this sub-division wise data and label them as district.

The variable we use is the rate of net migration, which is net migration divided by average population. Note that net migration is defined as: In-migration – Out-migration. So, positive net migration for a district in an inter-census period means more people moved in than moved out in that district in the given period. Similarly, negative net migration implies net out-migration. We are not able to distinguish between domestic and international migration from our estimates.

In all three inter-census years, net migration rate is negative at the aggregate level (Table 1). That is, out-migration dominates in-migration. Theoretically, in a closed economy, the aggregate rate should be zero. So, the negative rate may also imply out of the country migration. However, at the district level, net migration rates are both positive and negative (Table A1). Major districts where more people moved in than moved out are Gazipur, Jessore, Chuadanga, Meherpur, Jhenaidah and Kushtia. Districts where significant net out-migration occurred in the period 1991-2000 include Brahmanbaria, Madaripur , Kishoregonj, and Perojpur.

Note that Dhaka and Chittagong are the two biggest cities in Bangladesh and these two cities are the centres of economic activities. So, we exclude these urban growth centres from the sample. Also, planned settlement of the Bengali people has been taken place since 1980s in hilly districts such as Bandarban, Khagrachhari and Rangamati where most tribal non-Bengali people live. In this case, in-migration in these districts is not a response, rather an outcome of government policy. So, we also exclude these 3 districts from the sample. As expected, net in-migration is positive and large for all these 5 districts.[4] Therefore, we drop these 5 districts and run regressions and report the results in Tables 2-4.

4. Empirical Strategies

Regression model

$$\textit{Migration rate}_{i,t} = \beta_0 + \beta_1.\textit{Agricultural productivity}_{i,t} + \beta_2.\textit{ Damaged cropped area}_{i,t} + \beta_3.\textit{District dummy}_i + \beta_4.\textit{Period dummy}_t + u_{i,t}$$

Here the dependent variable is the net migration rate and agricultural productivity is the real agricultural revenue per capita. *i* and *t* denote district and inter-census periods respectively. There are other variables that also impact net migration, especially the pull factors such as rate of urbanization, change in growth centre, etc. Since these variables are not correlated with climatic variables, it does not affect the consistency of the estimate. However, agricultural productivity might be affected by natural disasters such as flood, drought, cyclones which in turn impact the net migration. So, we include share of damaged cropped area in total cropped area to avoid the omitted variable bias.

Identification Issues

In the above regression model, per capita real revenue can be endogenous. The endogeneity may arise due to omitted variable bias and simultaneity bias. Time invariant district specific characteristics such as soil quality can impact the agricultural productivity.[5] Districts also vary with respect to altitude and physiography (e.g., flood plains, basin, beels, tract, hills and terrace). In order to control for this time invariant heterogeneity, we use district fixed effects.[6] We also control for unobserved temporal effects using period dummies.

The migration rate may also impact per capita agricultural revenue. If agricultural labours migrate from a district (to another district or abroad) the productivity may decline and it may depress output and revenue. On the other hand, lower population leads to higher per capita income. So, the net effect is not unambiguous. So, we instrument agricultural productivity with the weather variables to address the simultaneity bias.

[4] Dhaka, the biggest growth centre of the country, saw the highest net in-migration rates in all three periods – 31 percent in 1974-1980, 20 percent in 1981-90 and 26 percent in 1991-2000. Chittagong, the second largest urban district, saw a moderate 5 percent net in-migration in 1991-2000. In the hilly districts Khagrachhari, Rangamati and Bandarban, net in-migration rates were 16 percent, 8 percent and 5 percent respectively. These statistics are not reported in Table 1 as this table corresponds to the regression sample of Table 2.

[5] There are three broad types of soil in Bangladesh – Flood plain soil, hill soil and terrace soil. There is a wide variation of quality within each group. For example, there are 14 types of flood plain soil found in flood prone districts (Agricultural Statistical Yearbook, 2011).

[6] We checked that within-variations in temperature and rainfall variables are significant to run district fixed effects. Please see Figures A1 and A2 in appendix.

The identifying assumption is that exogenous variations of weather variables impact migration rate only through agriculture. It is a plausible assumption because it is very unlikely that rural people in Bangladesh migrate because they do not like the local weather.

The first stage regression is:

$$\textit{Agricultural productivity}_{i,t} = \gamma_0 + \gamma_1.\ \textit{Weather variables}_{i,t} + \gamma_2.\ \textit{District dummy}_i + \gamma_3.\textit{Period dummy}_t + u_{i,t}$$

The weather variables include mean and standard deviation of temperature (maximum and minimum) and rainfall, as discussed in section 3. The unobserved characteristics of the districts might influence the migration rate and the agricultural productivity in the first stage as well. Therefore, we also control for unobserved spatial and temporal effects using district and period dummies respectively.

Since it is highly likely that the errors are correlated over time, that is, the assumption of i.i.d. does not hold, we need more realistic error structure. We assume that errors are correlated within district but not across districts. Therefore, in order to capture these within-district correlated errors we cluster the errors around district to get unbiased estimates of standard errors.

We run a battery of diagnostic tests for the validity of instruments. In order to test endogeneity we use Durbin-Wu-Hausman test where the null hypothesis is that the variable is exogenous. We also check the validity of the instruments (over identifying test) using Hansen's J-statistics. This is possible as we have more instruments than endogenous variables.

5. Regression Results and Discussions

Regression results are presented in Tables 2-4. Note that standard errors are clustered around districts for all models in all tables. Table 2 reports OLS and Fixed Effect results of the effect of agricultural productivity on net migration rate. The specifications vary with the extent of control for unobserved effects. We investigate whether important heterogeneity occurs at the district level and not just at the regional level and whether temporal heterogeneity is linear (time trend) or nonlinear (time dummies). The first two specifications (model 1 and 2) do not control for unobserved effects (OLS); next two specifications (model 3 and 4) control partial spatial effects with region dummies[7] and full temporal effect with year dummies; the following two specifications (model 5 and 6) control patrial temporal effect with time trend and full spatial effect with district dummies; and the last two specifications (model 7 and 8) control full spatial and temporal effects with district and year dummies respectively. Within the same level of control for unobserved effects, the specifications vary with control for agricultural damage due to disasters.

The FE results in Table 2 show that per capita real agricultural revenue is significant for the models 5-8, where district level unobserved effects are controlled for. The size of the significant coefficients varies from 0.0010 to 0.0014. It implies that about 1 standard deviation decrease in real per capita revenue increases net out-migration (net of in-migration) rate by 1 to 1.4 percent[8].

The Disaster variable is not found significant.

As discussed in section 4, the real per capita agricultural revenue can be endogenous because of reverse causality. Therefore, we run IV and instrument it by a host of weather variables. Table 3 reports the first stage regression results where we regress per capita real agricultural revenue on weather variables, controlling for district and year fixed effects. First we use all the weather variables - all averages and standard deviations of rainfall and temperature (model 1). Then we mechanically choose the set of weather variables with at least 10 percent level of significance using 'stepwise' command of STATA (model 2). We then search for the set of variables with 5 percent level of significance. But it has lower F-stat than the sets with 10 percent level of significance. So, we disregard this set of weather variables. Then we start manual search for higher F-stat using only average (model 3), only SD1 (model 4), only SD2 (model 5), both SD1 and SD2 (model 6), both average and SD1 (model 7) and finally both average and SD2 (model 8) of rainfall and temperature.

[7] There are 23 regions and these regions are older large districts.
[8] The standard deviation of real agricultural revenue for predominantly rural and non-tribal districts is 11.02.

Table 3 shows that an increase in average rainfall in dry season increases the real revenue per capita while over-month fluctuations (SD1) of rain in the wet season lowers it. An increase in both average maximum and minimum temperature in the wet seasons leads to higher productivity. However, monthly fluctuation (SD1) of minimum temperature in wet season decreases revenue. Over the year fluctuations (SD2) of minimum temperature in wet season is found to increase the per capita revenue.

Now we check how these models fare with respect to a host of diagnostic tests for instruments. First consider the F-statistics for the joint significance of the weather variables. F-statistics are highly significant for all models. For the models 4 and 7 the F-statistics are above the ten-point rule of thumb (Stock and Yogo, 2005). For model 4, it is also larger than the critical values for a 15 percent Wald Test, indicating that the instruments are not weak (Cragg and Donald, 1993)[9].

We also test for endogeneity and use Durbin-Wu-Hausman test where the null hypothesis is that the variable is exogenous. All the models, except for model 4, show that the null of exogeneity cannot be rejected. That is, there is no support for the endogeneity of real per capita revenue. However, the model 4 rejects the null at 9 percent level of significance. We also check the validity of the instruments (over identifying test) of this model 4. The Hansen's J-statistics show that the instruments of this model are not invalid, though the acceptance of the null is not very strong (p=0.13). For the IV, we only consider this model 4 where the set of instruments are only standard deviations of rainfall and temperature over months (SD1).

Table 4 reports the IV results. As in Table 2, we also control for partial and full unobserved temporal and spatial effects. It shows that for the models 5 and 6 the coefficients for per capita real revenue are positive and significant. The size of the coefficients is larger than the coefficient of FE model in Table 2. IV estimates were expected to lead to lower marginal impact on dependent variable. However, larger coefficient in the second stage is very common in IV estimations and it can be attributed to simultaneity bias in our case.

Note that in Table 4, the year dummy (1981-1990) is significant in model 6 while time trend used in models 3 and 4 are not significant, indicating that temporal heterogeneity is non linear. Though the coefficients of individual district and region dummies are not reported in the Tables 2-4, it is noteworthy that coefficients of some district dummies are statistically significant, implying that heterogeneity also occurs at the district level.

We use two statistically significant coefficients of weather variables – standard deviation (SD1) of rain in wet season and standard deviation (SD1) of minimum temperature in wet season –to calculate elasticities. Since we have not used log specifications, the coefficients are marginal impacts, not the elasticities. The coefficients of SD1 of rain in wet season (R, hereafter) and SD1 of minimum temperature in wet season (T, hereafter) are -0.03 and -13.89 respectively. Therefore, we can calculate elasticities of real per capita revenue with respect to R and T at the mean values. Note that mean values for R, T and Y (per capita real revenue) are 166.67 cm, 1.34 degree Celsius and 28.71 respectively for the period 1974-2000. At these mean values, elasticity of Y with respect to R, e(Y,R) = -0.17 and elasticity of Y with respect to T, e(Y,T)=-0.65. That is, a 1 percent increase in standard deviation (SD1) of rain in wet season decreases real revenue by about 17 percent. Similarly, a 1 percent increase in standard deviation (SD1) of minimum temperature in the wet season decreases per capita real revenue by about 65 percent.

Using the above elasticities, we can calculate the elasticities of the net migration rate (M) with respect to T and R. First we need to know the elasticity of M with respect to Y. From Table 4, we know that the marginal effect of Y on M is 0.0024 (model 6). In our studied sample, the mean value of net migration rate is -0.015. At this mean value, the elasticity of M with respect to Y, e(M,Y)=4.62 percent. That is, one percent decrease in real per capita revenue raises net out-migration by 4.62 percent. Therefore,

e(M,R) = e(Y,R) x e(M,Y) = 0.81 percent, and

e(M,T) = e(Y,T) x e(M,Y) = 3.00 percent

The calculations show that a 1 percent increase in standard deviation (SD1) of rainfall and a 1 percent increase in standard deviation (SD1) of minimum temperature in wet season result in about 0.81 percent and 3 percent increase in net out-migration rate respectively.

[9] The Wald test statistics is 9.05, which is not reported in Table 4.

Scientific models predict different likely scenario of changes in climatic variables for different forecasting horizons. IPCC (2001) reports that 0.5 to 2 degree Celsius increase in temperature is associated with 10 to 45 cm of sea level rise. These climatic changes will lead to inundation of about 15 percent of Sundarban areas. The World Bank (2000) projects that by the year 2030 sea level will rise by 30 cm and temperature in will increase by 0.7 degree Celsius in monsoon and 1.3 degree in winter seasons in Bangladesh. A recent report by World Bank (2013) also pictures multiple scenarios under 2 degree and 4 degree changes in temperature compared to pre-industrial level. FAO (2007) also predicts that temperature will increase by 1 degree Celsius in winter and 0.8 degree Celsius in summer by the year 2030. Similarly, rain fall will decrease by 1.2 mm in winter and increase by 4.7 mm in summer.

It would be a fruitful exercise if we can predict the possible migration scenario under different climatic conditions using our estimates. The combined effect of an incremental change in the SD of wet-season rainfall (ΔR) and an incremental change in the SD of wet-season minimum temperature (ΔT) on per capita real agricultural revenue (ΔY) is given by, $\Delta Y = \beta R \Delta R + \beta T \Delta T$, where βR and βT are regression coefficients from the first-stage regression. The effect on net migration rate is then $\Delta M = \gamma Y \Delta Y = \gamma Y\ [\beta R \Delta R + \beta T \Delta T]$, where γY is the regression coefficient on agricultural revenue from the second-stage regression.

Therefore, in order to forecast the future changes in migration rate we need forecasts on ΔR and ΔT. Most of the climate change scenarios deal with changes in mean temperature and rainfall. However, our empirical analysis shows that it is the fluctuation (standard deviation) of temperature and rainfall that impacts migration through agricultural productivity. A World Bank study (2000) predicts that fluctuation (standard deviation) of wet-season rainfall will be 11 percent higher in 2030 compared to 1990. According to Table 1, the standard deviation of wet-season rainfall in 1990 was around 169.375 (averaging the values for 1981-90 and 1991-2000). Hence, ΔR is 0.11×169.375.

Now we need a prediction about the fluctuation of temperature (ΔT). It is important to note that fluctuation of temperature is less studied than the fluctuation of rainfall in climate change models. To the best of our knowledge, there is no IPCC study on the forecast of the fluctuation of temperature. However, a very recent article in Nature by Huntingford et al. (2013) shows that while the global average of fluctuation (standard deviation) is fairly stable, there are some regions where it shows declining trends, including south Asian region. The models predict that the standard deviation of temperature will decrease by around 5-15 percent by 2030 in the south Asian region. Note that the prediction is about the average temperature while our variable of interest from the regression model is the SD of minimum temperature in wet season. Since there is no prediction available on the SD of minimum temperature in wet season, we use the prediction on average temperature. Note that SD of minimum temperature in the wet season also shows decreasing trend in our data (Table 1). We use the lower bound of the forecast which is 5 percent. From Table 1 we find that the SD of wet-season minimum temperature in 1990 was1.185 (averaging the values for 1981-90 and 1991-2000). Hence, ΔT is 0.05×1.185.

The effect of wet-season minimum temperature variability on per capita agricultural revenue is significant only at 10 percent. Moreover, forecasting on temperature variability is not widely studied. Therefore, we consider two cases: i) ΔT is zero and ii) ΔT is non-zero.

Case I: ΔT=0

The combined effect of changes in SD of rainfall and temperature is:

$$\Delta M = \gamma Y \Delta Y = \gamma Y\ [\beta R \Delta R + \beta T \Delta T] = \gamma Y \beta R \Delta R = -0.00136$$

So, $100 \times \Delta M/M = 22$ percent

The net out-migration rate will increase by 22 percent in 2030 compared to 1990 due to increase in variability of rainfall in wet season.

Case II: ΔT is non-zero

The combined effect of changes in SD of rainfall and temperature is:

$$\Delta M = \gamma Y \Delta Y = \gamma Y\ [\beta R \Delta R + \beta T \Delta T] = 0.00061$$

In this case, the positive effect (in-migration) of temperature variability dominates the negative effect of rainfall variability (out-migration).

So, $100 \times \Delta M/M = 10$ percent

The net in-migration rate will increase by 10 percent in 2030 compared to 1990 due to decrease in variability of minimum temperature and increase in variability of rainfall in wet season.

However, the above predictions are *ceteris paribus* predictions as they do not account for any behavioral responses by farmers or others beyond the short-run responses captured by our fixed-effect regression models.

6. Conclusion

A recent report of the Word Bank (2013) shows that world is now 0.8°C above pre-industrial levels of the 18th century and a 2°C world is highly likely in one generation. Higher temperature in winter, declining soil moisture and increasing drought in dry season, more variability in monsoon rain and greater salinity in soil in the south are likely scenarios for Bangladesh in a couple of decades. It is established that Bangladesh's drought-prone areas are warmer and drier than 50 years ago and current projections suggest that Bangladesh will become hotter and it will face frequent droughts due to increased rainfall variations. These changes of climatic variables have strong repercussion on agricultural productivity, poverty and food security. These adverse effects depress the income from agriculture of the rural people as well as the rural real wages. In these circumstances, in the absence of market based coping strategies such as credit and insurance markets and due to limited support from resource constrained governments in developing countries, affected people choose to migrate. In our study we investigate how climate induced changes in agricultural productivity impacts the rate of net migration.

This is the first study on Bangladesh which systematically investigates the impact of changes in climatic variables migration. This study particularly focuses on the agricultural channel: climatic changes influence agricultural productivity and income and changes in agricultural income impacts households' decision to migrate. We compile and create a unique district level data set on migration, agricultural productivity and climatic variables for three inter-census periods 1974-1980, 1981-1990 and 1991-2000. We run period and district fixed effect to control for unobserved heterogeneity. Since migration rate can also influence agricultural productivity, we also run IV. We instrument agricultural productivity with climatic variables. Our regression results show that reduction in real per capita revenue significantly increases the rate of net out-migration. We also make some predictions of the future migration patterns in Bangladesh based on the regression estimates. Following the prediction of the World Bank (2000) about rainfall variability, we show that fluctuation in rainfall in wet season will result in about 22 percent increase in net out-migration by the year 2030 compared to the rate of 1990. However, if we also assume non-zero temperature variability (5 percent decrease, according to a recent study), the effect reverses. In this case, compared to 1990, in-migration will increase by about 10 percent in 2030.

This study draws attention of the policy makers to the possible impact on mass movement of climate change. Climate change induced migration will put pressure on limited urban space and jobs, and create civic unrest. Therefore, it is important to formulate pragmatic adaptation policies and investments by the government and also by donor agencies so that migration decisions resulting from climate induced shocks can be influenced. Investment in research for developing heat, salinity and water resilient crops, developing institutions for agricultural credit and crop insurance, creating climate-shock free off-farm job opportunities in rural areas are potential tools for providing disincentives to migrate. These elements should be reflected in the national policies in Bangladesh such as 'National Action Plan on Adaptation' (NAPA) and the 'Bangladesh Climate Change Strategy and Action Plan' (BCCSAP) in order to better address climate change induced impact of agriculture on migration.

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Tables

Table 1: Descriptive statistics

Variables	1974-80	1981-1990	1991-2000
Net migration rate	-0.021	-0.001	-0.011
Ratio of damaged cropped area to total cropped area	0.031	0.081	0.091
Real agricultural revenue per capita	24.892	33.560	24.458
Average rainfall in dry season (cm)	56.397	61.041	66.657
Average rainfall in wet season (cm)	314.202	333.467	317.052
Average max. temperature in dry season (Celsius)	28.527	28.584	28.633
Average min. temperature in dry season (Celsius)	16.804	16.822	16.954
Average max. temperature in wet season (Celsius)	31.959	32.144	32.421
Average min. temperature in wet season (Celsius)	24.79	24.91	24.99
SD1 of rainfall in dry season (cm)	63.469	72.218	78.741
SD1 of rainfall in wet season (cm)	175.385	173.241	165.509
SD1 of max. temperature in dry season (Celsius)	2.912	2.781	3.092
SD1 of min. temperature in dry season (Celsius)	4.509	4.189	4.432
SD1 of max. temperature in wet season (Celsius)	1.198	1.187	1.183
SD1 of min. temperature in wet season (Celsius)	1.269	1.342	1.320
SD2 of rainfall in dry season (cm)	32.619	48.786	51.787
SD2 of rainfall in wet season (cm)	53.293	63.027	51.111
SD2 of max. temperature in dry season (Celsius)	0.267	0.480	0.337
SD2 of min. temperature in dry season (Celsius)	0.345	0.419	0.242
SD2 of max. temperature in wet season (Celsius)	0.367	0.380	0.409
SD2 of min. temperature in wet season (Celsius)	0.289	0.323	0.418

Table 2: Effect of agricultural productivity on net migration rate

Dependent variable: Rate of net migration

Variables	model 1	model 2	model 3	model 4	model 5	model 6	model 7	model 8
Per capita real agricultural revenue	0.0008	0.0008	0.0011	0.0011	0.0010*	0.0011*	0.0013*	0.0014*
	(0.0005)	(0.0005)	(0.0007)	(0.0007)	(0.0005)	(0.0006)	(0.0007)	(0.0007)
Damaged cropped area		-0.1076		0.0245		-0.0622		-0.0279
		(0.0911)		(0.2647)		(0.2339)		(0.2759)
Year dummy 1974-80			0.0124	0.0138			0.0124	0.0108
			(0.0167)	(0.0301)			(0.0194)	(0.0331)
Year dummy 1981-90			-0.0014	-0.0012			-0.0033	-0.0036
			(0.0087)	(0.0090)			(0.0098)	(0.0103)
Trend					-0.0006	-0.0004		
					(0.0010)	(0.0015)		
Constant	-0.0389*	-0.0314	-0.0433***	-0.0443*	1.1894	0.8233	-0.0478***	-0.0466*
	(0.0198)	(0.0227)	(0.0161)	(0.0232)	(1.9166)	(2.9607)	(0.0176)	(0.0244)
Region dummy	No	No	Yes	Yes	No	No	No	No
District dummy	No	No	No	No	Yes	Yes	Yes	Yes
Observations	177	177	177	177	177	177	177	177
R-squared	0.0162	0.0208	0.1243	0.1244	0.4046	0.4051	0.4070	0.4071

Clustered standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3: First stage regression

Dependent variable: per capita real agricultural revenue

	All weather variables	Step-wise search	Only Average	Only SD1	Only SD2	SD1 and SD2	Average and SD1	Average and SD2
VARIABLES	**model 1**	**model 2**	**model 3**	**model 4**	**model 5**	**model 6**	**model 7**	**model 8**
Avg. rain in dry	0.3103***	0.3749***	0.4387***				0.5353***	0.3496***
	(0.1028)	(0.0884)	(0.0910)				(0.0951)	(0.0908)
Avg. rain in wet	0.0059		-0.0464				-0.0018	-0.0452*
	(0.0248)		(0.0284)				(0.0332)	(0.0268)
Avg. max. temp. in dry	1.7299		10.6467				9.6249	14.8663*
	(8.0647)		(10.9489)				(11.9471)	(8.2150)
Avg. min temp. in dry	-2.8626		-7.0549				-13.1958*	-5.1164
	(5.1621)		(5.7778)				(6.8447)	(5.3706)
Avg. max. temp. in wet	21.0055***	18.2706***	11.8471				12.7576	9.7519
	(7.5632)	(3.7987)	(7.3019)				(9.2038)	(6.2007)
Avg. min. temp. in wet	15.476*		14.1531*				17.8861*	12.6658
	(7.945)		(7.8184)				(9.2929)	(7.6758)
SD1 of rain in dry	0.0586			0.1061		0.0582	-0.0251	
	(0.1048)			(0.0764)		(0.0937)	(0.1177)	
SD1 of rain in wet	-0.0723*	-0.0745***		-0.0304**		-0.0664	-0.0522	
	(0.0398)	(0.0253)		(0.0114)		(0.0470)	(0.0557)	
SD1 of max. temp. In dry	1.1280			2.7512		-10.2638	15.1144	
	(16.9764)			(14.8464)		(13.2614)	(13.0887)	
SD1 of min. temp. in dry	-6.9252			-16.7485		-8.7781	-16.0170	
	(14.2146)			(13.3232)		(11.7569)	(14.6886)	
SD1 of max temp. in wet	-4.7457			7.7739		8.8913	-2.9892	
	(8.6003)			(6.8034)		(7.4160)	(7.6237)	
SD1 of min temp. in wet	-30.2434**	-24.2398*		-13.8965*		-9.1657	-18.0277	
	(14.1639)	(13.0349)		(7.7161)		(15.0963)	(16.7738)	
SD2 of rain in dry	0.0731				0.0838	0.0704		0.0760
	(0.0764)				(0.0715)	(0.0862)		(0.0678)
SD2 of rain in wet	-0.0223				0.0084	0.0092		-0.0372
	(0.0551)				(0.0488)	(0.0437)		(0.0499)
SD2 of max. temp. in dry	-0.3803				7.5937	9.4979		6.6566
	(13.3368)				(14.9309)	(13.8318)		(13.3064)
SD2 of min. tempt. In dry	-10.9699	-14.8183			-25.6462**	-22.3924*		-16.4421
	(12.4813)	(11.8225)			(11.9793)	(12.7935)		(11.5272)
SD2 of max. tempt. In wet	2.7599				3.3791	-0.1631		4.6843
	(15.6175)				(13.6374)	(16.2986)		(14.1810)
SD2 of min. temp. in wet	36.5213***	31.3716**			21.9806**	33.1152***		22.5675*
	(12.1953)	(12.3267)			(10.5285)	(12.0585)		(12.3319)
Year dummy 1974-80	19.9185***	16.3855***	10.8408***	2.8272	7.3477*	8.1830	15.3488***	16.6609***
	(5.2441)	(3.2996)	(3.7132)	(4.2436)	(3.7344)	(5.4071)	(4.8626)	(4.6734)
Year dummy 1981-90	23.0912***	23.2982***	16.0308***	7.3493	15.4407***	11.3302	17.1466***	20.4317***
	(7.5206)	(3.1291)	(2.5929)	(6.0071)	(3.4309)	(7.9613)	(5.9831)	(4.0404)
District dummy	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-612.4899***	-552.0577***	-894.6253***	69.8741	7.6684	71.0748	-839.9521***	-955.2102***
	(218.1281)	(119.5625)	(257.0220)	(50.2039)	(8.1516)	(45.1070)	(282.8080)	(244.4534)
Joint significance of the weather variables: F-stat (p-value)	6.65 (0.000)	7.49 (0.000)	8.30 (0.000)	11.95 (0.000)	7.85 (0.000)	7.43 (0.000)	10.69 (0.000)	7.38 (0.000)
Endogeneity test: Chi-sq (p-value)	0.147	0.274	0.359	0.088	0.781	0.429	0.662	0.139
Validity test: Hansen J (p-value)	0.000	0.004	0.065	0.126	0.00	0.005	0.00	0.033
Observations	174	174	174	174	174	174	174	174
R-squared	0.7686	0.7591	0.7409	0.6840	0.6973	0.7164	0.7567	0.7587
Clustered standard errors in parentheses								

*** p<0.01, ** p<0.05, * p<0.1

P values of endogeneity test and validity tests are from second stage regressions which are not reported here, except for model 4. The second stage results for model 4 are reported in Table 5.

Table 4: Effect of agricultural productivity on net out- migration (FE with IV)

Dependent variable: Rate of net migration

VARIABLES	model 1	model 2	model 3	model 4	model 5	model 6
Per capita real agricultural revenue	-0.0012	-0.0020	0.0007	0.0008	0.0020*	0.0024*
	(0.0035)	(0.0042)	(0.0008)	(0.0011)	(0.0011)	(0.0013)
Damaged cropped area		0.1203		-0.0560		-0.1800
		(0.3647)		(0.2339)		(0.2290)
Year dummy 1974-80	0.0111	0.0174			0.0159	0.0061
	(0.0148)	(0.0330)			(0.0179)	(0.0269)
Year dummy 1981-90	0.0203	0.0284			-0.0390	-0.0477*
	(0.0330)	(0.0417)			(0.0262)	(0.0288)
Trend			-0.0006	-0.0004		
			(0.0008)	(0.0013)		
Constant	0.0079	0.0193	1.1621	0.8471	-0.1275**	-0.1366**
	(0.0731)	(0.0742)	(1.5635)	(2.6988)	(0.0614)	(0.0651)
Region dummy	Yes	Yes	No	No	No	No
District dummy	No	No	Yes	Yes	Yes	Yes
Observations	174	174	174	174	174	174
R-squared	0.0579	0.0096	0.4041	0.4056	0.3108	0.2649
Clustered standard errors in parentheses						

*** p<0.01, ** p<0.05, * p<0.1

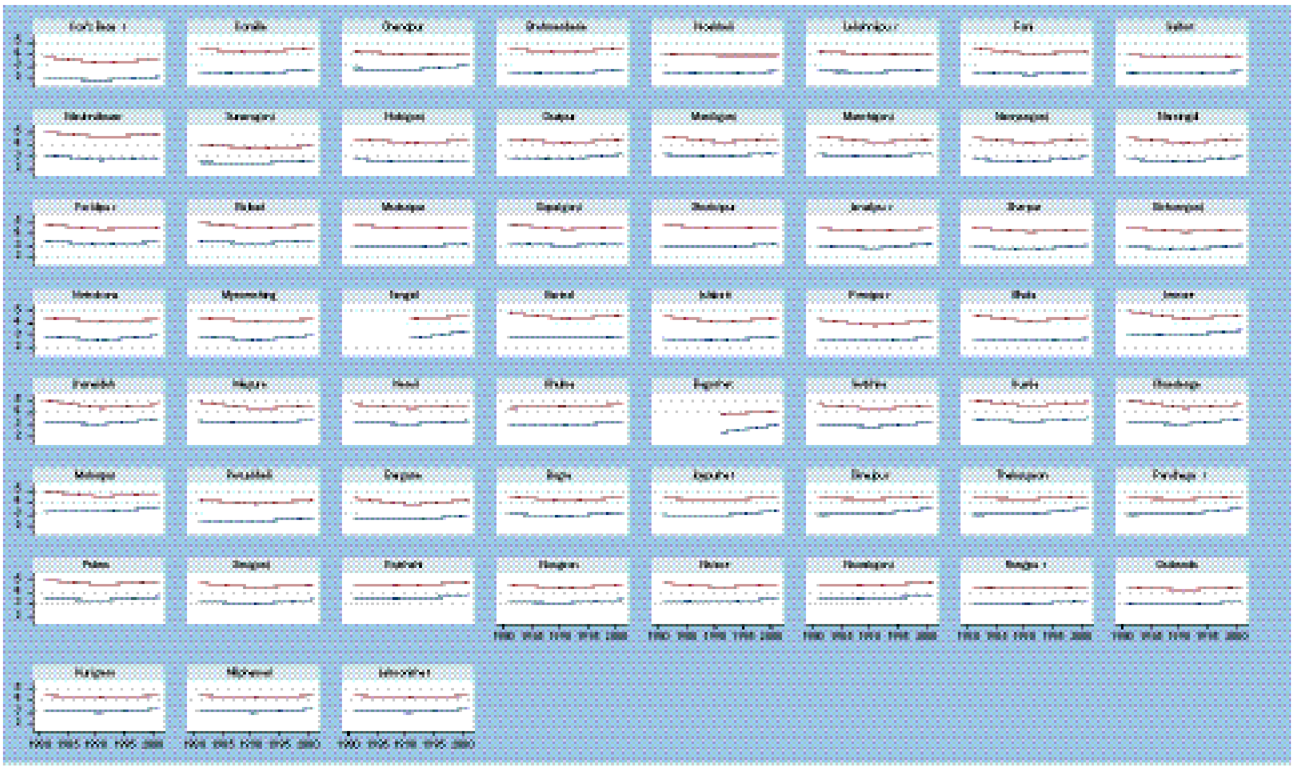
Here the instruments correspond to the model 4 of first stage regression (Table 4) where the set of instruments are only standard deviations of rainfall and temperatures over months (SD1).

Figures

Figure A1: District wise trends in SD1 of rainfall in dry (lower one) and wet season (upper one)

Year

Figure A2: District wise trends in SD1 of minimum (upper one) and maximum temperature (lower one) of dry season



Year

Appendix

Table A1: District wise rate of net migration

District	1974-1980	1981-1990	1991-2000
Cox'z Bazar	-0.0099	0.0174	-0.0425
Comilla	0.5337	-0.0445	-0.0580
Chandpur	-0.5314	-0.0807	-0.0633
Brahmanbaria	-0.0236	-0.0335	-0.0940
Noakhali	0.0234	-0.0050	-0.0494
Lakshmipur	-0.1486	-0.0679	-0.0658
Feni	-0.0156	-0.0101	-0.0527
Sylhet	-0.0016	-0.0076	-0.0299
Maulavibazar	0.0162	-0.0168	-0.0230
Sunamgonj	-0.0036	-0.0347	-0.0590
Hobigonj	-0.0024	-0.0295	-0.0534
Gazipur	-0.2571	0.1175	0.0991
Manikgonj	-0.0281	-0.0386	-0.0001
Munshigonj	-0.0240	-0.0557	-0.0317
Narayangonj	0.1160	0.0466	0.0673
Narsingdi	0.0807	-0.0026	-0.0353
Faridpur	-0.0146	-0.0120	-0.0081
Rajbari	0.0005	-0.0514	-0.0027
Madaripur	-0.0201	-0.0817	-0.0965
Gopalgonj	-0.0198	-0.0828	-0.0728
Shariatpur	-0.0179	-0.0982	-0.0603
Jamalpur	0.0011	-0.0047	-0.0315
Sherpur	-0.2180	0.1246	-0.0557
Kishoregonj	-0.0018	-0.0529	-0.0838
Netrokona	-0.0273	-0.0304	-0.0572
Mymenshing	0.0047	-0.0230	-0.0658
Tangail	0.0013	0.0234	-0.0238
Barisal	0.0105	-0.0081	-0.0769
Jalakati	-0.0072	-0.0145	-0.0792
Perojpur	-0.0204	-0.1175	-0.0812
Bhola	-0.0389	-0.0400	-0.0755
Jessore	0.0443	0.0340	0.0411
Jhenaidah	-0.0442	0.0297	0.0266
Magura	-0.0047	-0.0016	0.0020
Narail	0.0060	-0.0389	-0.0633
Khulna	0.0776	-0.0153	0.0447
Bagerhat	0.0017	0.0257	-0.0480
Satkhira	-0.0101	-0.0119	0.0099
Kustia	-0.0014	0.0310	0.0283
Chuadanga	0.0213	0.0497	0.0870
Meherpur	0.0212	0.0550	0.0721
Patuakhali	-0.0056	-0.0526	-0.0154
Barguna	-0.0133	-0.0541	-0.0212
Bogra	0.0129	0.0250	0.0076
Joypurhat	0.0018	0.0242	0.0058
Dinajpur	0.0161	0.0038	0.0070
Thakurgaon	0.0364	-0.0052	0.0062
Panchagar	-0.0201	-0.0262	-0.0091
Pabna	0.0068	0.0011	-0.0063
Sirajgonj	-0.0092	-0.0282	0.0135
Rajshahi	0.0731	0.0488	0.0592
Noagaon	0.0793	0.0006	-0.0153
Natore	0.0162	0.0475	-0.0211
Nawabgonj	-0.1317	0.0113	0.0024
Rangpur	-0.0423	0.0060	0.0103
Gaibanda	-0.0436	-0.0476	-0.0539
Kurigram	0.0814	-0.0720	-0.0546
Nilphamari	-0.0277	-0.0675	-0.0382
Lalmonirhat	-0.0911	-0.0104	-0.0214

Table A2: Calculation of net migration for Comilla district

Population in Bangladesh				Population in Comilla district		Ten year forward survival ratio	Expected survivor in 2001 in Comilla	Net migration in Comilla	Net migration rate in Comilla
Age group	1991	Age group	2001	1991	2001				
(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)=(iv)/(ii)	(viii)=(ii) x (vii)	(ix)=(vi)-(viii)	(x)=(ix) / ((v)+(vi)/2)
0-4	1.7E+07	10-14	1.6E+07	738168	645080	0.906	668923	-23843	-0.034
5-9	1.8E+07	15-19	1.2E+07	717012	452620	0.680	487644	-35024	-0.060
10-14	1.3E+07	20-24	1.1E+07	485845	360680	0.845	410642	-49962	-0.118
15-19	8933162	25-29	1.1E+07	319282	319860	1.204	384563	-64703	-0.202
20-24	8817412	30-34	8748460	298726	274740	0.992	296390	-21650	-0.076
25-29	9054070	35-39	7998320	303479	248640	0.883	268092	-19452	-0.070
30-34	6592716	40-44	6200100	220051	211140	0.940	206946	4194	0.019
35-39	5986031	45-49	4601160	209099	152860	0.769	160724	-7864	-0.043
40-44	4613327	50-54	4001600	168567	149560	0.867	146215	3345	0.021
45-49	3562365	55-59	2356440	132398	85000	0.661	87579	-2579	-0.024
50-54	3105517	60-64	2828640	119995	110880	0.911	109297	1583	0.014
55-59	1949721	65-69	1443140	75189	56340	0.740	55653	687	0.010
60+	5702765	70+	3318560	244855	147500	0.582	142486	5014	0.026
All	1.1E+08		9.1E+07	4032666	3214900			-210254*	-0.058

Note: * This is the column sum – summation over all age groups.

Table A3: District wise trends in real per capita agricultural revenue

District	1974-1980	1981-1990	1991-2000
Cox'z Bazar	33.105	25.593	15.073
Comilla	27.440	30.593	19.303
Chandpur	9.482	25.915	20.992
Brahmanbaria	19.516	40.035	22.632
Noakhali	43.619	26.098	13.413
Lakshmipur	20.558	22.546	13.537
Feni	32.618	23.373	12.487
Sylhet	19.855	21.864	15.733
Maulavibazar	30.369	25.738	18.735
Sunamgonj	33.003	30.516	14.372
Hobigonj	27.389	29.457	18.174
Gazipur	31.399	39.015	30.171
Manikgonj	16.857	34.083	46.232
Munshigonj	9.485	31.562	43.233
Narayangonj	9.323	20.017	23.824
Narsingdi	19.286	30.106	32.828
Faridpur	12.997	33.726	30.841
Rajbari	11.847	32.638	28.922
Madaripur	12.851	29.938	25.168
Gopalgonj	14.801	29.532	20.095
Shariatpur	14.375	33.783	24.160
Jamalpur	30.640	41.709	26.941
Sherpur	36.249	43.280	23.210
Kishoregonj	28.542	38.544	15.615
Netrokona	33.880	52.454	26.034
Mymenshing	30.735	42.622	18.089
Tangail	49.923	37.798	22.398
Barisal	19.360	18.243	10.347
Jalakati	20.609	22.477	14.583
Perojpur	20.549	21.441	14.641
Bhola	28.176	29.185	15.635
Jessore	21.484	43.765	28.574
Jhenaidah	24.660	34.695	33.351
Magura	22.736	54.417	43.340
Narail	17.670	30.897	34.461
Khulna	15.569	17.085	13.979
Bagerhat	25.138	26.473	20.835
Satkhira	22.624	36.122	20.975
Kustia	13.189	25.010	23.482
Chuadanga	14.851	35.788	33.572
Meherpur	14.179	75.050	50.537
Patuakhali	30.566	35.261	23.566
Barguna	32.648	34.576	23.819
Bogra	22.361	41.106	23.416
Joypurhat	42.457	45.108	37.028
Dinajpur	31.896	40.863	29.785
Thakurgaon	53.383	38.623	36.643
Panchagar	34.668	58.176	45.254
Pabna	15.054	24.517	23.106
Sirajgonj	17.079	28.111	18.416
Rajshahi	17.278	23.249	15.448
Noagaon	25.660	41.311	28.066
Natore	17.188	29.270	24.053
Nawabgonj	23.449	23.866	19.265
Rangpur	50.969	48.023	32.063
Gaibanda	25.356	47.827	30.544
Kurigram	59.564	51.194	40.245
Nilphamari	28.667	57.465	45.321
Lalmonirhat	26.940	56.530	42.156

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