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Weather Variability, Agricultural Revenues and Internal Migration: Evidence from Pakistan

Heman D. Lohano

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Contents

Abstract

Migration is a widely used adaptation response to climate and weather variability. In this paper, we investigate how variability in weather affects migration through the agricultural channel. We estimate an instrumental variables regression model that allows us to isolate the impacts of weather from other drivers of migration and analyze the impact of weather-driven changes in the crop revenue per hectare on the in-migration rate. We use panel data for 50 districts of Pakistan and four time periods, 1971–76, 1976–81, 1988–93, and 1993–98, and estimate a two-way error components model, controlling for unobserved district-specific and time-specific effects. Results show that temperature has a nonlinear effect, i.e., as temperature increases, the crop revenue per hectare initially increases and then declines. Furthermore, a 1 °C increase in the variability (standard deviation) of temperature reduces expected crop revenue per hectare by around 7.5 percent. The instrumental variables regression results show that a 1 percent weather-driven decrease in the crop revenue per hectare induces, on average, a 2 to 3 percent decrease in the in-migration rate into a district. Predicted increases in temperature and its variability during 2016–2035 (relative to 1971–1998) are likely to decrease crop revenues in relatively warm districts and increase them in cooler districts. These effects would decrease the in-migration rate in 18–32 districts (36–64 percent) and increase the rate in the remaining 18–32 districts. Thus, the extent and scope of the impacts of weather variability on migration in Pakistan depend on a district's geographic location and the variability of temperature in the future.

Keywords: Migration, weather variability, climate change, agriculture, panel data model, instrumental variables regression, Pakistan

Weather Variability, Agricultural Revenues and Internal Migration: Evidence from Pakistan

1. Introduction

Migration is a phenomenon observed the world over. Household migration decisions are influenced by 'push' and 'pull' factors as well as network effects. Favorable characteristics associated with the target destination of migrants are referred to as 'pull' factors and unfavorable characteristics associated with the origin are 'push' factors. Network factors support the households' decisions by providing them with the information, assistance, and encouragement necessary to survive in the new locale (Lee, 1966; Martin and Zurcher, 2008). The drivers of migration decisions can also be broadly categorized into economic, political, social, demographic and environmental factors (Grote and Warner, 2010; Black *et al.*, 2011).

Among the environmental factors, increasingly there is a focus on climate and weather related migration (Barrios *et al.*, 2006; Brown, 2008; McLeman, 2013). According to a recent report by the Intergovernmental Panel on Climate Change (IPCC), migration is a widely used adaptation strategy and the climate change will likely have significant impacts on human mobility (Adger *et al.*, 2014). In particular, Asia and the Pacific region could undergo migration and displacement on an unprecedented scale in the coming decades (Asian Development Bank, 2012). There is increasing recognition that climate change induced migration may compromise human security (Adger *et al.*, 2014) and may contribute to a range of problems such as unmanaged regional development, deterioration of ecosystems, conflicts and riots (Reuveny, 2007; Barbieri *et al.*, 2010; Feng *et al.*, 2010; Bhavnani and Lacina, 2015). Thus, for purposes of policy planning, there is a need for sound and robust predictions of climate induced migration (Lilleør and Van den Broeck, 2011).

Displacement and migration decisions can be triggered by weather events such as flooding or slower processes that contribute to loss of agricultural productivity (Brown, 2008). Climate and weather related migration is multi-faceted and migration depends on both vulnerability and the ability to migrate, as populations vulnerable to the climate change impacts may have the least ability to migrate (Black *et al.*, 2013). Adger *et al.* (2014) observe that the climate events have a significant impact on displacement, but most of the displacement is temporary as displaced people are likely to return to their original places. While weather events have serious implications for human displacement and security, this is not the focus of our paper. Rather, we are interested in examining how changes in weather variability affect migration by influencing economic drivers such as agricultural productivity.

As the literature on climate and weather related migration grows, increasingly there is a focus on exposing the link between climate and drivers of migration (Perch-Nielsen *et al.*, 2008), particularly economic drivers. Lilleør and Van den Broeck (2011) reviewing studies on the impacts of climate change on migration in less developed countries argue that important economic drivers, such as wage difference between origin and destination areas, are not very well understood. Their review indicates that most studies find linkages among climatic variables and migration, but these studies do not identify the channels through which climate variables affect migration. This is a serious gap in the literature that renders it impossible to make reliable and robust predictions about migration.

The clearest evidence of the impacts of weather variability is found in the agricultural sector. Weather variables are inputs into agriculture production and changes in climate have the largest effects on agriculture relative to other sectors (Deschenes and Greenstone, 2007). In this context, Feng *et al.* (2010) is an important study that estimates the impact of weather-driven changes in crop yields on international migration from Mexico to the United States. Feng *et al.* (2010) forecast that 2 to 10 percent of adult Mexicans may migrate to the United States by the year 2080 as a result of climate induced changes in agriculture. Complementing this work, Marchiori *et al.* (2012) show how weather anomalies induce internal migration that subsequently triggers international migration. Similarly, Feng *et al.* (2012), Iqbal and Roy (2015) and Viswanathan and Kavi Kumar (2015) establish how weather can influence migration through the agriculture channel. Estimates by Feng *et al.* (2012) suggest that climate change could induce nearly four percent of the adult population in rural counties in the US Corn Belt to migrate in the medium term (2020-2049). Iqbal and Roy (2015) predict that an increase in rainfall variability would increase net out-migration rates in Bangladesh by as much as 20 percent in 2030.

Pakistan is one of the most vulnerable countries in the world to climate change (UNDP, 2015). According to Global Climate Risk Index 2015 report, Pakistan is among the top ten most affected countries in the world during the period 1994–2013. It is ranked number five among the most financially affected countries in the world (with average annual losses of around 4 billion USD-PPP from climate change) during these two decades (Kreft *et al.*, 2015). Thus, in the future, climate and weather variability are likely to create a great deal of uncertainty about agricultural production as well as additional migration.

Agriculture is a very important sector in Pakistan and migration is a vital labor issue. Thus, several researchers have tried to un-tangle the determinants of migration. For instance, Barkley (1991), investigating the factors affecting inter-district migration during 1971-1980, shows that labor clearly moves towards districts with better socio-economic conditions. Other studies by Khan and Shehnaz (2000), Oda (2007), Mahmud *et al.* (2010) and Sarwar and Sial (2011) show how different socio-economic determinants, such as education and unemployment rate, influence migration. Yet, few studies ask how weather variability may affect migration patterns. The exception is Mueller *et al.* (2014), who use data from 583 households in four districts of Pakistan, to show the effect of heat stress on the probability of men and women moving out of villages. They estimate the effect of temperature on farm and non-farm income and find that extreme temperature has much higher impact on farm income relative to nonfarm income.

In our study, we ask how weather variability may affect migration by inducing changes in agricultural productivity and the economic sectors that depend on agriculture. Much has been written about the effect of extreme weather such as floods on peoples' in Pakistan (Kirsch *et al.*, 2012). While extreme weather is an important driver, it is equally important to understand how slower changes induced by weather motivate human mobility in the long run. Thus, we investigate how weather related migration occurs because of changes in economic drivers that are linked to agriculture. Based on an instrumental variable regression approach (Feng *et al.*, 2010), we examine how weather variables affect agricultural productivity and how this, in turn, induces inter-district migration in Pakistan. We organize a unique data set of migration, agricultural and weather, drawing on census and meteorological information from 50 districts over four 5-year time periods (1971–76, 1976–81, 1988–93, and 1993–98). Our focus is on internal migration as most migration is generally internal. For instance, according to UNDP (2009), internal migrants in the world are almost four times as many as international migrants.

We find robust evidence showing that weather-driven changes influence district-level in-migration rates in Pakistan by affecting crop revenues. Temperature increases are likely to decrease the crop revenue per hectare in relatively warm districts and increase the same in relatively cool districts. Furthermore, temperature variability has adverse effects on the crop revenue per hectare. Through these effects on crop productivity, weather variables have a significant nonlinear effect on the in-migration rate. The extent and scope of such impacts in the future depend mainly on temperature variability and the geographic location of districts.

2. Model and Estimation Methods

2.1 Modeling the Weather-Migration Interface

Agriculture is the one most vulnerable to climatic changes as weather variables including temperature and precipitation are direct inputs into agriculture production (Deschenes and Greenstone, 2007). Thus, the conceptual framework of this study hinges on two issues: the impact of changes in weather variables on agricultural productivity and how this, in turn, triggers the movement of labor resulting in inter-district migration in Pakistan.

The impacts of weather variability and climate change on agriculture have been studied worldwide, including in Pakistan (Cline, 2007; Kavi Kumar, 2009; Janjua *et al.*, 2010; Dinar and Mendelsohn, 2011; Ahmed and Schmitz, 2011). Such impacts are especially significant for Pakistan, where agriculture accounts for 21 percent of GDP and 44 percent of employment. The agriculture sector has strong backward and forward linkages with other sectors (Government of Pakistan, 2014a). Many industries, such as textile and food processing, are agro-based and are directly or indirectly linked to it. Furthermore, other remaining sectors are also affected because household consumer demand is dependent on agro-based income. Thus, weather variables have both direct and indirect impacts on the overall economy through the agriculture sector.

The second consideration underlying this paper is that weather-driven changes in agricultural productivity can trigger the movement of labor resulting in inter-district migration in Pakistan. The impact of changes in weather on agriculture may vary such that it may be favorable in some locations while it may be unfavorable in others. As discussed in the recent IPCC report by Hijioka *et al.* (2014), who observe that warming temperature would lead wheat yield to increase in some parts of Pakistan but a decrease in other parts of the country. Massetti and Mendelsohn (2011) investigated the impact of climate change in different states of the United States and found that the farms in relatively cool locations would benefit while those in warmer locations would likely to be hurt. Due to the linkages of agriculture sector with the other sectors, as discussed above, if agriculture does well because of favorable weather then the overall district economy does well and this lures workers from other districts.

Migration is an adaptation strategy adopted by households whose livelihoods are put at risk by climatic changes (Dillon *et al.*, 2011; Adger *et al.*, 2014). Migration is often a proactive strategy adapted keeping in view current weather events as well as anticipation of such events in the future (Bardsley and Hugo, 2010). For wage earners, when there is a decline in wages, we can expect labor to move out of a location to another where wages may be higher. Expected wage differentials between locations are regarded as the main motivation for migration (Todaro, 1969). This demand-supply framework for labor works as expected in Pakistan, where there is generally a free flow of labor.

The district-level Census data in Pakistan show that the total stock of migrants from other districts constituted around 8.4 percent of the total population in 1998 (Government of Pakistan, 1998). Internal migration includes rural-rural, rural-urban, urban-urban, and urban-rural migration and is comprised both intra-district and inter-district migration. Based on the Pakistan Integrated Household Survey data, Memon (2005) observes that migration due to economic reasons in the year 1997–98 included 31 percent rural-rural, 42 percent rural-urban, 20 percent urban-urban, and 7 percent urban-rural migration in Pakistan. Weather variability could trigger migration not only to work in agriculture, but also to work in a host of jobs that are directly or indirectly linked as unskilled workers, in particular, can switch from one sector to another.

For purposes of investigating the impact of weather variability on agricultural productivity and how this, in turn, triggers the internal migration we follow Feng *et al.* (2010). For our analyses, we use crop revenue per hectare as a measure of agricultural productivity and in-migration rate as an indicator of migration.[1] We estimate the effect of weather variables on crop revenues per hectare and the effect of weather-driven changes in crop revenue per hectare on in-migration rate. We examine the linkages among weather variables, agriculture and migration using an instrumental variables (IV) regression model specified in equations (1) and (2) below:

$$M_{it} = G(\beta_0 + \beta_1 \ln R_{it} + a_i + \lambda_t + \varepsilon_{it}) \qquad (1)$$

$$\ln R_{it} = \alpha_0 + \alpha_1 T_{it} + \alpha_2 T_{it}^2 + \alpha_3 P_{it} + \alpha_4 P_{it}^2 + \alpha_5 SDT_{it} + \alpha_6 SDP_{it} + v_i + w_t + u_{it} \qquad (2)$$

where i subscript is index for districts in Pakistan (i = 1, 2,..., 50) and t subscript is index for 5-year time periods (1971–76, 1976–81, 1988–93 and 1993–98). M_{it} is in-migration rate which measures a flow of additional migrants in district i that migrated from other districts in a 5-year period as a proportion of the district i population ($0 < M_{it} < 1$). $G(.)$ is a function taking on values strictly between zero and one. R_{it} denotes crop revenue per hectare per year in 1000 Pakistan rupees (PKR), which is the value of crop yields and a measure of agricultural productivity of land. T_{it} represents mean temperature in°C, and P_{it} represents mean precipitation in meters per year. SDT_{it} denotes the standard deviation of temperature across 5 years and SDP_{it} denotes standard deviation of precipitation across 5

[1] Alternative measures of migration such as out-migration and net migration are not considered because Pakistan census data contain information on only in-migration. Out-migration could be computed through a residual approach, however, data on district level birth and death rates are not available in Pakistan.

years. Finally, a_i and v_i denote district-specific effects that are time-invariant, λ_t and w_t denote time-specific effects that are district-invariant, and ε_{it} and u_{it} denote stochastic disturbance terms.

Equation (1) is a statistical model that regresses the in-migration rate on crop revenue per hectare with district-specific effects, and time-specific effects. The parameter of interest is β_1, which measures the semi-elasticity of the in-migration rate with respect to crop revenue per hectare. This model controls for unobserved time-invariant confounders at the district level (district-specific effects) and unobserved confounders affecting all districts in the same period (time-specific effects). An econometric problem with the above model is that crop revenue per hectare (R_{it}) may be correlated with the error term (ε_{it}), which makes R_{it} an endogenous variable. This endogeneity may be due to omitted variables or from simultaneity, that is, the revenue per hectare may affect migration, but migration may also affect revenue per hectare. To address the problem of endogeneity, we use weather variables as instrumental variables for the revenue per hectare, specified in equation (2), to control for potential endogeneity. Theoretically, this approach is statistically valid for determining the causal effect of crop revenue per hectare on migration (Auffhammer and Vincent, 2012). Through this approach, only variations in revenue per hectare that are associated with weather variables are used to estimate the effect of revenue per hectare on in-migration rate. Thus, this approach allows us to isolate the effect of weather variables from other drivers of migration (Feng *et al.*, 2010).

We estimate the above model separately using two different measures for the crop revenue per hectare: based on major crops (wheat, rice, cotton and sugarcane) and based on wheat crop only. In section 3, we provide details on measuring the revenue per hectare as well as weather variables for each case.

2.2 Functional Form

In equation (1), the dependent variable, in-migration rate, is measured as a proportion and bounded between zero and one. We identify a specific functional form for this equation which ensures that predicted migration rate is within the bounds. Following Baum (2008), equation (1) is re-written with $G(.)$ as a logistic function that takes the value of function between zero and one:

$$M_{it} = \frac{\exp(\beta_0 + \beta_1 \ln R_{it} + a_i + \lambda_t + \varepsilon_{it})}{1+\exp(\beta_0 + \beta_1 + \ln R_{it} + a_i + \lambda_t + \varepsilon_{it})} \tag{3}$$

Further, equation (3) can be re-written as linear in parameters:

$$y_{it} = \beta_0 + \beta_1 \ln R_{it} + a_i + \lambda_t + \varepsilon_{it} \tag{1'}$$

where

$$y_{it} = \ln\left(\frac{M_{it}}{1-M_{it}}\right)$$

Thus, the above IV regression model is estimated using equation (1') in place of equation (1). For this, we first compute y_{it} using the values of M_{it} and equation (4). The variable y_{it} is defined only if M_{it} is strictly between zero and one. Since the values of M_{it} are strictly between zero and one in the data of this study, y_{it} is defined for all observations in the dataset.

The above model of our study is based on a model proposed by Feng *et al.* (2010) but we extend it in three major ways. Firstly, in Feng *et al.* (2010), the dependent variable migration rate is treated without bounds. As migration rate is measured in proportion, it must be bounded between zero and one. In our model, we identify a functional form for the migration equation, which ensures that the predicted migration rate is bounded between zero and one. Secondly, they use crop yield as a driver for migration. However, a household's decision to migrate may be affected by monetary incentives. A lower crop yield may be associated with higher price. Therefore, our model uses monetary value of crop yields. Finally, Feng *et al.* (2010) estimated the model without controlling for unobserved time-specific effects (Auffhammer and Vincent, 2012). It may cause omitted variable bias if the unobserved time-specific effects are not included. In our study, we estimate the panel data model with two-way error components controlling for both the unobserved cross-section specific effects and time-specific effects.

2.3 Estimation Methods

For estimating the IV regression model in equations (1') and (2), the district-specific effects and time-specific effects can be regarded as being either fixed or random. The time-specific effects control for variables that are changing over time but are common among all districts, such as technology and the monetary, fiscal and other government policies. Since the data are only for a very small number of time periods (four), which do not represent a random sample across time, fixed effects are used for time-specific effects (Baltagi, 2008). We also use fixed effects for the district-specific effects because the unobserved heterogeneity at the district level may be correlated with the explanatory variables. For example, soil quality varies across districts and is likely to be correlated with agricultural productivity. Furthermore, the districts are not a random sample as we use data from all the districts of Pakistan for which data are available. Therefore, we use fixed effects to control for both district-specific effects and time-specific effects. We estimate the model using the limited information maximum likelihood (LIML) estimator and the two stage least squares (TSLS) estimator. For making inferences, we use heteroskedasticity and autocorrelation (HAC) robust standard errors. We conduct various diagnostic tests in order to check the validity of IV regression and instruments, discussed in section 4 along with their results.

3. Data and Descriptive Statistics

This study uses panel data for 50 districts of Pakistan for four time-periods: 1971–76, 1976–81, 1988–93 and 1993–98. This section describes the sources of data, methods used for construction of variables, and descriptive statistics.

3.1 Migration

We obtain migration data for each district of Pakistan from the two latest population census reports (Government of Pakistan, 1981, 1998). The 1981 Census Report provides migration data for two 5-year periods (1971–1976 and 1976–1981) and the 1998 Census Report provides migration data for the two 5-year periods of 1988–1993 and 1993–1998.[2] For each district, the reports provide data only on in-migration, which is defined as the number of persons who moved into the district from other districts or countries in each of the time periods. The data, however, do not include the number of persons who moved within the district. We compute the in-migration rate as follows:

$$M_{it} = \frac{MI_{it}}{(Pb_{it} + Pe_{it})/2} \tag{5}$$

where MI_{it} is the number of people in district *i* that migrated from other districts in 5-year period *t*, Pb_{it} is total population in district *i* in the beginning of period *t*, and Pe_{it} is the total population in district *i* at the end of period *t*. Computation in equation (5) requires population data for the following years: 1971, 1976, 1981, 1988, 1993 and 1998. Since district-wise population data are available only for the years in which the census was conducted, i.e., 1972, 1981 and 1998, we use inter-censual population annual growth rate to estimate the population for the remaining years:

$$g = \left(\frac{PC_T}{PC_0}\right)^{\frac{1}{T}} - 1 \tag{6}$$

where PC_0 and PC_T denote population in two census years for computing inter-censual annual growth rate.[3]

In Pakistan, there are four provinces, viz., Balochistan, Khyber Pakhtunkhwa, Punjab and Sindh, and four other administrative units, viz., Islamabad Capital Territory (ICT), Gilgit-Baltistan, FATA (Federally Administered Tribal

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2 Migration data are not available for the period 1982-1987 because of the delay in conducting the 1991 Census, which came to be conducted only in 1998. In addition to the Census Reports, migration data are also available in the Labor Force Surveys. Since the Labor Force Surveys however are designed for computing provincial and national level statistics and are based on sampling methods, we use data only from the Census Reports, which provide district level data and are not based on sampling.

3 We use the growth rate between 1972 and 1981 for estimating population in 1971 and 1976, and the growth rate between 1981 and 1998 for estimating population in 1988 and 1993.

Areas), and Azad Jammu and Kashmir (Government of Pakistan, 2014b; see Figure 1 for a map of Pakistan). The provinces and other administrative units are further divided into districts. In Pakistan, the boundaries of some districts have changed over time. Thus, while there were only 73 districts in the year 1981, there were 119 districts in the year 1998. We have addressed the issue of changing district boundaries as follows. In the case of districts with changing boundaries, the data show that the district has been split into two or three districts from 1981 to 1998. Since the 1998 Census Report also provide the information on migrants' previous districts of residence, we convert these split districts into the big district by summing up the number of migrants in these split districts and subtracting the number of migrants whose previous residence was one of these split districts.

The merging of districts results in a total of 71 cross-section observations (districts or merged districts) with consistent boundaries from 1981 to 1998.[4] We dropped 16 of the 71 observations as migration data for these districts are not reported in the census reports. These districts are controlled by tribes, and data from which have never been collected due to both the law and order situation in the areas and the lack of an established record system. The panel data on migration are therefore only available for 55 districts or merged districts for these 5-year periods: 1971–76, 1976–81, 1988–93 and 1993–98. A detailed examination of the data indicated that 5 of the 55 districts for which we had data were highly urbanized and were not agricultural based (including Karachi, Lahore, Peshawar, Quetta, and Rawalpindi). Thus, we excluded these 5 districts from the study sample. The analysis therefore uses data for 50 districts and for four time periods with 200 total observations (see Appendix A for a list of these districts or merged districts).

3.2 Revenue per Hectare

We collected the data on production and area for each crop in each district from the government publications (Government of Pakistan, Various years, 2010). We obtained the data on the nominal prices of crops in Pakistan in LCU (local currency units) per tonne from the database of the Food and Agricultural Organization of the United Nations (FAOSTAT, 2014). We compute the real prices of crops in 1998 PKR by deflating the nominal price using CPI (consumer price index) reported by the State Bank of Pakistan (2010).

We compute the revenue per hectare in PKR 1,000 for each district using data from four major crops of Pakistan, viz., wheat, rice, cotton and sugarcane, which are very common crops in Pakistan. Wheat accounted for 51 percent of total net area sown while these four major crops accounted for 64 percent of the total cropped area in Pakistan in the year 1997-98 (Government of Pakistan, 2014a). For each district, we compute the revenue per hectare per year for each 5-year period as follows:

$$R = \frac{\sum_{\tau=1}^{5} \sum_{c=1}^{4} (Price_{c\tau} \times Production_{c\tau})}{\sum_{\tau=1}^{5} \sum_{c=1}^{4} Area_{c\tau}} \tag{7}$$

where $Price_{c\tau}$ denotes the real price of crop c in PKR 1,000 per tonne in year τ, $Production_{c\tau}$ denotes the production of crop c in tonnes in year τ, and $Area_{c\tau}$ denotes the total area sown for crop c in hectares in year τ. As mentioned in section 2, we estimate the model separately using two different measures for the crop revenue per hectare: based on major crops (wheat, rice, cotton and sugarcane) and based on wheat crop only. So, for wheat crop, the revenue per hectare is computed using equation (7) based on only wheat crop.

3.3 Weather

We obtained data on mean temperature and precipitation for each month from 1971 and 1998 for various stations from the Pakistan Meteorological Department. There are 50 districts in the panel data, which are covered via 29 weather stations by the Pakistan Meteorological Department during the study period. For the districts where the weather stations are not located within the district boundaries, we assign the nearest weather station or the average of the nearest ones, as reported in the district census reports (Government of Pakistan, 1981, 1998).

[4] Although there were 73 districts in 1981, merging with consistent boundaries from 1981 to 1998 was possible for 71 districts due to formation of new districts.

There are two main cropping seasons in Pakistan, namely *Rabi* (from November to April) and *Kharif* (from May to October). Wheat is grown in *Rabi* while rice and cotton are grown in *Kharif*. Sugarcane is grown during the months from both seasons. First, we construct all weather variables given in equation (2) for each season. We first compute the mean temperature during all the months of the season for each season. We then compute the average temperature per season for each 5-year period, and compute standard deviation of temperature across 5 years. Similarly, we compute the precipitation during each season by adding the precipitation during each month of the season. We then compute the average precipitation per season for each 5-year period, and compute standard deviation of precipitation across 5 years. For analysis with wheat crop only, we use weather variables constructed for the *Rabi* season. For analysis with four major crops, we construct annual measures using variables from both seasons. For annual temperature, we take the average of temperature in two seasons. For annual precipitation, we add precipitation in two seasons. For each temperature and precipitation, annual measure of standard deviation is computed as the square root of the sum of variances in two seasons, where the variance is the square of standard deviation.

3.4 Descriptive Statistics

The descriptive statistics of the variables used in the model are presented in Table 1. The in-migration rate is measured as a flow variable with a 5-year time period. The statistics on the in-migration rate in Table 1 indicate that, on average, 1.3 percent of the district population migrated into the district from other districts within the 5-year time period. At the aggregate level, the average revenue per hectare has increased over time from 1971–76 to 1993–98 in case of both major crops and wheat. This is mainly due to technological change and government policy of price support. Note that we control for such time-specific effects in addition to district-specific effects in our model. During this period, all weather variables including temperature, precipitation and their standard deviations (annual and *Rabi* season) have increased over time at the aggregate level.

The district level heterogeneity of data is illustrated in histograms in Figures 2–4, which present the distribution of in-migration rate, revenue per hectare and the selected weather variables. The distribution of the migration rate is skewed right, indicating a higher migration rate in relatively fewer districts.[5] Revenue per hectare approximates to a normal distribution in both major crops and wheat (Figure 3). The distribution of precipitation in the *Rabi* season is skewed right as rainfall is rare during the winter (Figure 4).

4. Results and Discussion

4.1 Regression Results

In this section, we present and discuss the results of the IV regression model. In addition to controlling for potential endogeneity, the IV regression model explains the changes in the in-migration rate that result from the weather-driven changes in the revenue per hectare from crops. We use two different measures of revenue per hectare: based on major crops and wheat only. In the case of major crops, weather variables are measured on annual basis, while for wheat, weather variables are measured for *Rabi* season. We estimate the models using the LIML and TSLS estimators. In all regressions, we construct test statistics that are HAC robust.

Table 2 presents the IV regression results using revenue per hectare based on major crops, and reports the results for the two stages along with the diagnostic tests. In the first stage results in panel A, we estimate the impact of weather variables on revenue per hectare. Specification 1 includes weather variables on both temperature and precipitation. The results show that temperature and its squared term are statistically significant at 1 percent and 5 percent, respectively. We find that the relationship between the revenue per hectare and temperature is quadratic, i.e., as temperature increases, revenue per hectare initially increases, reaches at the peak, and then declines. This result is in line with Kolstad (2010) and Shakoor *et al.* (2011) for the case of Pakistan. The standard deviation of temperature is statistically significant at the 5 percent level and the sign of estimated coefficient is negative, as expected. If the standard deviation of temperature increases by 1 °C, the expected value of crop revenue per hectare would decrease by around 7.5 percent. In specification 1 (Table 2), the precipitation related variables are

[5] Appendix B presents the over-time pattern of in-migration rate at the district level.

not statistically significant. Thus, we also estimate the model without the precipitation-related variables, using only three weather variables related to temperature, as specification 2. However, we find that the results are very similar. Note that the first stage results are the same with LIML and TSLS estimators.

The second stage results in panel B of Table 2 are the IV regression results that show the relationship between the in-migration rate and revenue per hectare for each specification. The coefficient on the revenue per hectare is positive and statistically significant at the 1 percent level for both specifications as well as with both the LIML and TSLS estimators. As explained above, the IV model estimates the impact of weather-driven changes in the revenue per hectare on in-migration rate. The LIML results show that a 1 percent increase (decrease) in crop revenue productivity in a district driven by weather variables induces around 2.3 percent (or 0.03 percent points) increase (decrease) in the in-migration rate into a district on average. In the two specifications, the estimate is between 2.2–2.3 percent with LIML estimator and 1.9–2 percent with TSLS, indicating that results are robust to first-stage specifications and IV estimation methods.

Thus, the regression results show that temperature has nonlinear effect on crop productivity (quadratic relationship). As the relationship between migration rate and revenue per hectare is direct, through its effects on crop productivity, the temperature also has a nonlinear impact on the in-migration rate. This result confirms and complements the previous work by Bohra-Mishra (2014), who find similar evidence for Indonesia. We find that it is not only the average temperature but also its fluctuations (measured by the standard deviation) that have the impacts on migration through the agriculture channel. Similar evidence has been obtained by Iqbal and Roy (2015) for Bangladesh.

The results of diagnostic tests to examine the validity of the IV regression and instruments are reported in panel C of Table 2. First, we test whether it is necessary to use IV estimation. For this, we test whether the independent variable, the revenue per hectare, is exogenous or endogenous, using Chi-square test that is HAC robust version of Durbin-Wu-Hausman test (Baum *et al.*, 2010). As the p-value of the Chi-square test is much less than 0.01, the test rejects the null hypothesis of its exogeneity at the 1 percent level, indicating that revenue per hectare is endogenous variable and justifying the estimation of IV regression.

Next, we examine the validity of instruments. As there are more instruments than endogenous regressors, we conduct Hansen's J test of over-identifying restrictions, which examines the exogeneity of instruments. As the model has one endogenous regressor, the test assumes that at least one instrument is exogenous and then examines the exogeneity of all other instruments (Stock and Watson, 2011: 454). As the p-value from the Hansen J statistic is much greater than 0.1, the test fails to reject the null hypothesis that the instruments are exogenous for all four regressions. To test whether the instruments are relevant (not weak), we conduct the weak identification test using the Kleibergen-Paap Wald F test (Kleibergen and Paap, 2006), which is HAC robust version of Cragg-Donald test. The test results show that the F statistic is larger than the critical values for a 15 percent maximal LIML size, with a 5 percent significance level (Stock and Yogo, 2005), indicating that the instruments are not weak for both specifications with the LIML estimator. For the TSLS estimator, however, the test does not reject the null of weak instruments even at 30 percent maximal IV relative bias, with a 5 percent significance level. Note that if the instruments are weak, LIML is much superior to TSLS (Stock and Yogo, 2005: 106), and LIML is more nearly centered and its confidence intervals are more reliable than the TSLS (Stock and Watson, 2011: 466). We also conduct a weak instruments robust test for β_1 (the coefficient on endogenous variable – revenue per hectare) using Moreira's (2003) conditional likelihood ratio (CLR) test. The CLR test is a preferred test when there is a single endogenous explanatory variable, and it is valid whether the instruments are strong, weak or even irrelevant (Stock and Watson, 2011: 465–466). As the p-value in the CLR test is much less than 0.01, the coefficient on the revenue per hectare is statistically significant at the 1 percent level and thus the IV results are valid.

Table 3 presents the results using revenue per hectare for wheat crops. We find very similar results as above. Temperature and its squared term are statistically significant at 1 percent – as temperature increases, revenue per hectare initially increases, reaches at the peak, and then declines. Results on the impact of the standard deviation of temperature are also similar.

In the second stage results, the coefficient on the revenue per hectare is positive and statistically significant at the 1 percent for both specifications as well as with both LIML and TSLS estimators. Results of specification 1 with LIML estimator show that a 1 percent increase (decrease) in wheat revenue productivity in a district driven by weather variables induces around 3.2 percent (or 0.04 percent points) increase (decrease) in the in-migration rate into a district, on average. Finally, the results of diagnostics tests are also similar with wheat crop as compared to those with major crops. Thus, our results are also robust to crops selected for measuring the crop productivity per hectare.

Finally, we also examine the validity of our IV regression results by examining the reduced-form regression results (Angrist and Pischke, 2009: 157). In this regression, we estimate the relationship between the in-migration rate and weather variables using the ordinary least square method with HAC robust standard errors. The reduced-form regression results are reported separately for major crops and wheat in Appendix C. Temperature and its square term are jointly statistically significant at 5 percent and 1 percent with major crop and wheat, respectively. Standard deviation of temperature is statistically significant, and the sign of estimated coefficient is negative, as expected. Precipitation related variables are jointly statistically significant at 1 percent with wheat only. All weather variables are jointly statistically significant at 1 percent with both major crop and wheat, indicating causal relation between migration rate and weather variables in the reduced form.

4.2 Projections

In this section, we estimate the possible consequences of future weather variability on internal migration through agriculture channel in Pakistan using the results of our IV regressions. We estimated the models based on two separate measures of revenue per hectare (major crops and wheat crop) using corresponding weather variables. For projections, we use estimates based on wheat because wheat is produced in all districts in the sample dataset. Other crops such as rice, cotton and sugarcane can be produced only in certain locations depending on the soil conditions and agro-climatic zones. Also note that each crop has different growing seasons, and has different sensitivities to weather variations. In our dataset, wheat accounts for 67 percent of the total area under the selected major crops. The total revenue from wheat and major crops are highly correlated, which is equal to 0.95. For projections, we use LIML estimation of specification 1 based on revenue per hectare from wheat (Table 3), which includes weather variables on both temperature and precipitation.

Descriptive statistics in Table 1 show that the average temperature in *Rabi* season has increased by 0.5°C and the standard deviation of temperature has increased by 0.3°C from 1971–76 to 1993–98. To estimate the possible consequences of future weather variability on internal migration flows in Pakistan, we make use of near-term climate projections.

According to the Government of Pakistan (2013), Pakistan is expected to be warmer by 0.24 to 0.51°C per decade depending on the emission scenarios. According to the Fifth Assessment Report of the IPCC (Kirtman *et al.*, 2013: 982), the average temperature in Pakistan is expected to rise by 0.75 to 2°C, and the standard deviation of temperature is expected to rise by 0.5 to 1°C during the period 2016–2035 relative to the reference period 1986–2005.[6] Keeping in view the above projections, we assume 1°C increase in the average temperature in *Rabi* season and three different scenarios including 0.5, 0.75 and 1°C increase in the standard deviation of temperature for examining the impact of future weather variability during 2016–2035 relative to the reference period 1971–1998. We assume no change in precipitation variables.

For projections, first, we compute the predicted values of the revenue per hectare ($\hat{R}_{it}$) using the first stage results and observed data on weather variables. Using the second stage results, we compute the predicted values of in-migration rate ($\hat{M}_{it}$) using $\hat{R}_{it}$. We compute the mean values across four time periods for both the revenue per hectare and the in-migration rate to get their baseline values for each district: $\hat{R}_{i0}$ and $\hat{M}_{i0}$. Next, for each scenario, we change the weather data by adding the assumed changes in weather variables, and similarly compute the mean predicted values of the revenue per hectare and the in-migration rate for each district as the projected values: $\hat{R}_{ip}$ and $\hat{M}_{ip}$. Finally, for each district, we compute the rate of change from the baseline to projected values as:

$\Delta \hat{R}_i = (\hat{R}_{ip} - \hat{R}_{i0}) / \hat{R}_{i0}$ and $\Delta \hat{M}_i = \hat{M}_{ip} - \hat{M}_{i0}$.

6 These weather projections are for the winter season (December to February), which is part of the *Rabi* season (November to April).

As discussed in the regression results, the relationship between revenue per hectare and temperature is quadratic, and standard deviation of temperature has negative effect on the revenue per hectare. Figure 5 illustrates this relationship for specification 1 based on wheat. As the temperature increases, the revenue per hectare initially increases, reaches at the peak, and then declines. An initial increase in wheat revenue per hectare is expected because cold stress is unfavorable in the plant physiological processes for crop growth (Sultana *et al.*, 2009). However, as temperature further increases, these benefits are exhausted. In our analyses, the peak in wheat revenues occurs at an average temperature of 21.4°C. As temperature further increases, we can expect a fall in yields. Wheat yields can decrease because of a reduction in the growth period and length of crop life cycle due to accelerated phenology under higher air temperatures (Sultana *et al.*, 2009). High temperature at the reproductive stages impedes normal grain development resulting in reduced grain size and yield losses (Sultana *et al.*, 2009; Hossain *et al.*, 2011). In addition to these direct effects, high temperature also indirectly affects crop growth through its effects on moisture status and pest and disease incidence (Sivakumar and Stefanski, 2011). Data show that 4 districts out of 50 districts (8 percent), which belong to Sindh province, namely Badin, Hyderabad, Tharparkar and Thatta, are relatively warm in the *Rabi* season with average temperature above the threshold level (21.4°C), and are already experiencing lower wheat revenue per hectare than the optimum.[7] As the relationship between in-migration rate and revenue per hectare is direct, weather variables have a nonlinear effect on the in-migration rate through its effects on crop productivity. We examine below the implications of this result for the projections.

The predicted impact of each of the three scenarios on the revenue per hectare and the in-migration rate through agricultural channel is presented in Figures 6 and 7. Results show that, when we increase temperature by 1°C and the standard deviation of temperature by 0.5°C, the revenue per hectare decreases in 18 districts, although it increases in the remaining 32 districts (scenario 1, Figure 6). As there is a direct relationship between the revenue per hectare and in-migration rate, the projected change in weather variables leads the in-migration rate to decrease in 18 districts and increase in 32 districts (scenario 1, Figure 7). The 18 districts adversely affected by rise in temperature and its standard deviation are relatively warm districts including 3 districts from Balochistan province, 3 districts from Punjab province, and all 12 districts from Sindh province (Figure 8). These 18 districts (indicated by 0 and 1 in Figure 9) are located in southern part of the country and include 4 districts, located on the southern border, that are already experiencing lower wheat revenue per hectare than the optimum.

When we increase temperature by 1°C and the standard deviation of temperature by 0.75°C, the revenue per hectare and the in-migration rate decrease in 23 districts and increase in 27 districts (scenario 2, Figures 6 and 7). When we increase temperature by 1°C and the standard deviation of temperature by 1°C, the revenue per hectare and in-migration rate decrease in 32 districts and increase in 18 districts (scenario 3, Figures 6 and 7). Thus, higher variability in temperature is likely to expand adverse effects from southern parts to north-eastern parts of Pakistan (Figure 9). The simulation results show that, due to quadratic relationship between crop yields and temperature, 18–32 districts (36–64 percent), which are relatively warm, are likely to be hurt and the remaining districts may benefit with rise in projected temperature and its variability in the near-term future. This result confirms and complements previous work discussed in the recent IPCC report by Hijioka *et al.* (2014), who observe that warming temperature would lead wheat yield to increase in some parts of Pakistan but decrease in other parts of the country. Similarly, Massetti and Mendelsohn (2011) investigated the impact of climate change in different states of the United States and found that the farms in relatively cool locations would benefit while those in warmer locations would likely to be hurt.

As some districts are likely to benefits while others to be hurt, we also computed the overall impact on Pakistan by examining the total revenue in all districts, which is equal to the sum of the revenue across all district, where revenue in each district is equal to wheat area times revenue per hectare in each district. We find that the overall total revenue per year is predicted to change by 1.4, –0.5 and –2.3 percent under scenarios 1, 2 and 3, respectively. Thus, the overall revenue may increase or decrease in Pakistan depending on the future variability in the temperature. Under all scenarios, predicted changes in temperature and its variability are likely to induce migration, as some districts would be better off while other would be worse off.

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[7] Data show that the wheat revenue per hectare has increased in all districts due to technological change but it increased by only 19 percent (from PKR 10,414 to 12,429) in these 4 districts and by 40 percent (from PKR 9,381 to 13,116) in the remaining 8 districts of Sindh from 1971–1981 to 1988–1998. Thus, over this time period, the revenue per hectare in these 4 districts turned into 6 percent lower than the other districts in 1988–1998 (from 11 percent higher in 1971–1981).

There are many drivers of migration such as socioeconomic conditions and various pull and push factors. Note that we use an IV regression approach that isolates the weather impacts from other drivers of migration (Feng *et al.*, 2010). Thus, the projected impacts on migration are the partial impacts associated with projected weather and agricultural scenarios, keeping other drivers of migration constant. Thus, the projected impacts on migration do not account for other derivers of migration.

5. Conclusions and Policy Implications

Meteorological information for the period 1971-76 to 1993-98 in Pakistan shows that the average temperature across 50 districts increased by 0.5°C during the *Rabi* season. These districts also saw an increase in the variability (standard deviation) of temperature by 0.3°C during this period. According to the Fifth Assessment Report of the IPCC (Kirtman *et al.*, 2013: 982), the average temperature in Pakistan is expected to rise by 0.75 to 2° and the variability of temperature is expected to rise by 0.5 to 1°C, during the period 2016–2035 relative to the reference period 1986–2005. Given these predictions, this study asks whether weather variability may impact inter-district migration by affecting agricultural productivity and the economic sectors that depend on agriculture in Pakistan.

Statistical analyses show that weather-driven changes in revenue per hectare have a significant impact on the in-migration rate in districts of Pakistan. A weather-driven 1 percent decrease in the crop revenue per hectare in a district induces a 2 to 3 percent decrease in the in-migration rate into a district. Thus, as crop revenues decline, the labor migration rate into a district declines. This change in migration can be attributed to reduction on labor demand on farms and in other agriculture related sectors.

While crop revenues and the in-migration rate move in the same direction, temperature and crop revenues have a quadratic relationship. Thus, as temperature increases, crop revenues initially increase, reach a peak, and then declines. If we examine wheat crops, an initial increase in crop revenue is likely because cold stress is unfavorable in the plant physiological processes for crop growth (Sultana *et al.*, 2009). However, as temperature further increases, these benefits are exhausted. As temperatures increase even further, we can expect a fall in yields because of a reduction in the growth period and length of crop life cycle due to accelerated phenology under higher air temperatures (Sultana *et al.*, 2009). In our analyses, the peak in wheat revenues occurs at an average temperature of 21.4°C. Interestingly, this level of temperature has already been reached in four districts.

Simulation results show that predicted rise in temperature and its variability is likely to decrease the wheat revenue per hectare in relatively warm districts, located in south, and increase it in relatively cool districts, located in the northern part of Pakistan. Through its effect on the crop revenue per hectare, increases in temperature and its variability during 2016–2035 are likely to induce the in-migration rate to decrease in 18–32 districts (36–64 percent) and increase in the remaining 18–32 districts (relative to 1971–1998). Thus, weather variability will have a significant impact on the internal migration through the agriculture channel in the case of Pakistan. However, in-migration increases or decreases will depend on the geographic location of the districts.

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Tables

Table 1: Descriptive statistics

Variable	Definition	Observations	Overall Mean	1971–76	1976–81	1988–93	1993–98
In-migration rate [%]	Flow of In-migrants in 5-years divided by population	198	0.0132 [1.32%] (1.17)	0.0119 [1.19%]	0.0225 [2.25%]	0.0058 [0.58%]	0.0127 [1.27]
Major Crops							
Revenue per hectare from major crops	Average revenue per hectare per year from four major crops (PKR 1000)	193	11.95 (4.00)	10.56	10.26	12.63	14.14
Temperature	Average temperature in 5 years (°C)	200	23.36 (3.57)	23.27	23.52	23.29	23.37
SD of Temperature	Standard deviation in annual temperature across 5 years (°C)	200	0.94 (0.60)	0.90	0.67	1.05	1.16
Precipitation	Average precipitation per year in 5 years (meters)	200	0.53 (0.33)	0.43	0.58	0.57	0.56
SD of Precipitation	Standard deviation in annual precipitation across 5 years (meters)	200	0.026 (0.01)	0.022	0.028	0.026	0.030
Wheat							
Revenue per hectare from wheat	Average revenue per hectare per year from wheat (PKR 1000)	193	10.25 (3.65)	7.75	8.56	11.11	13.26
Temperature in *Rabi*	Average temperature in *Rabi* season in 5 years (°C)	200	17.13 (3.90)	16.86	17.36	17.00	17.31
SD of temperature in *Rabi*	Standard deviation in temperature in *Rabi* season across 5 years (°C)	200	0.67 (0.48)	0.64	0.40	0.72	0.93
Precipitation in *Rabi*	Average precipitation in *Rabi* season in 5 years (meters)	200	0.18 (0.23)	0.14	0.19	0.22	0.17
SD of Precipitation in *Rabi*	Standard deviation in precipitation in *Rabi* season across 5 years (meters)	200	0.01 (0.01)	0.007	0.012	0.013	0.008

Note: Standard deviations are in parentheses.

Table 2: Instrumental variables regression results based on major crops

Variables	LIML		TSLS	
	Specification 1	Specification 2	Specification 1	Specification 2
A. Stage 1: Dependent Variable: ln(R) (Revenue per hectare from major crops)				
Constant	–6.925**	–6.429**	–6.925**	–6.429**
	(3.014)	(2.692)	(3.014)	(2.692)
Temperature	0.642***	0.612***	0.642***	0.612***
	(0.241)	(0.219)	(0.241)	(0.219)
Temperature^2	–0.011**	–0.010**	–0.011**	–0.010**
	(0.005)	(0.005)	(0.005)	(0.005)
SD of Temperature	–0.075**	–0.074**	–0.075**	–0.074**
	(0.032)	(0.030)	(0.032)	(0.030)
Precipitation	0.576		0.576	
	(0.539)		(0.539)	
Precipitation^2	–0.321		–0.321	
	(0.378)		(0.378)	
SD of Precipitation	0.797		0.797	
	(2.902)		(2.902)	
District FE and Time FE	Yes	Yes	Yes	Yes
Observations	191	191	191	191
R^2	0.799	0.796	0.799	0.796
B. Stage 2: Dependent variable: Logit transformation of in-migration rate				
Constant	–9.892***	–10.067***	–9.086***	–9.417***
	(1.765)	(1.831)	(1.270)	(1.417)
ln(*R*) (from major crops)	2.249***	2.334***	1.853***	2.015***
	(0.847)	(0.888)	(0.605)	(0.685)
District FE and Time FE	Yes	Yes	Yes	Yes
Observations	191	191	191	191
R^2	0.704	0.693	0.748	0.731
C. Diagnostic Tests				
Endogeneity Test: Chi-square stat [p-value]	9.295 [0.002]	10.959 [0.001]	9.295 [0.002]	10.959 [0.001]
Over-identification test: Hansen J stat [p-value]	3.801 [0.578]	2.934 [0.231]	4.296 [0.508]	3.190 [0.203]
Weak instruments test: Kleibergen-Paap Wald F-stat	3.422	6.204	3.422	6.204
Stock-Yogo critical value (15% maximal LIML size)	3.34	4.36		
Stock-Yogo critical value (30% maximal TSLS relative bias)			5.15	5.39
Weak instruments robust test: CLR [p-value]	16.68 [0.001]	17.10 [0.0002]	16.68 [0.001]	17.10 [0.0002]

Notes: *, ** and *** denote significance at 10%, 5% and 1%, respectively. HAC robust standard errors are in parentheses.

Table 3: Instrumental variables regression results based on wheat

Variables	LIML		TSLS	
	Specification 1	Specification 2	Specification 1	Specification 2
A. Stage 1: Dependent Variable: ln(R) (Revenue per hectare from wheat)				
Constant	−2.040* (1.098)	−1.017 (1.015)	−2.040* (1.098)	−1.017 (1.015)
Temperature in *Rabi*	0.402*** (0.119)	0.315*** (0.112)	0.402*** (0.119)	0.315*** (0.112)
(Temperature in *Rabi*)^2	−0.009*** (0.003)	−0.008** (0.003)	−0.009*** (0.003)	−0.008** (0.003)
SD of Temperature in *Rabi*	−0.075** (0.035)	−0.070* (0.037)	−0.075** (0.035)	−0.070* (0.037)
Precipitation in *Rabi*	1.322* (0.771)		1.322* (0.771)	
(Precipitation in *Rabi*)^2	0.400 (0.635)		0.400 (0.635)	
SD of Precipitation in *Rabi*	−5.581 (4.816)		−5.581 (4.816)	
District FE and Time FE	Yes	Yes	Yes	Yes
Observations	191	191	191	191
R^2	0.832	0.819	0.832	0.819
B. Stage 2: Dependent variable: Logit transformation of in-migration rate				
Constant	−11.479*** (2.685)	−12.398*** (3.520)	−9.568*** (1.391)	−10.472*** (1.950)
ln(R) (from wheat)	3.247** (1.385)	3.731** (1.844)	2.241*** (1.385)	2.717*** (1.014)
District FE and Time FE	Yes	Yes	Yes	Yes
Observations	191	191	191	191
R^2	0.633	0.558	0.750	0.701
C. Diagnostic Tests				
Endogeneity Test: Chi-square stat [p-value]	8.847 [0.003]	8.571 [0.003]	8.847 [0.003]	8.571 [0.003]
Over-identification test: Hansen J stat [p-value]	7.436 [0.190]	3.587 [0.166]	10.145 [0.071]	4.520 [0.104]
Weak instruments test: Kleibergen-Paap Wald rk F-stat	4.026	4.618	4.026	4.618
Stock-Yogo critical value (15% maximal LIML size)	3.34	4.36		
Stock-Yogo critical value (30% maximal TSLS relative bias)			5.15	5.39
Weak instruments robust test: CLR [p-value]	22.63 [0.0000]	15.71 [0.0003]	22.63 [0.0000]	15.71 [0.0003]

Notes: *, ** and *** denote significance at 10%, 5% and 1%, respectively. HAC robust standard errors are in parentheses.

Figures

Figure 1: Map of administrative units of Pakistan

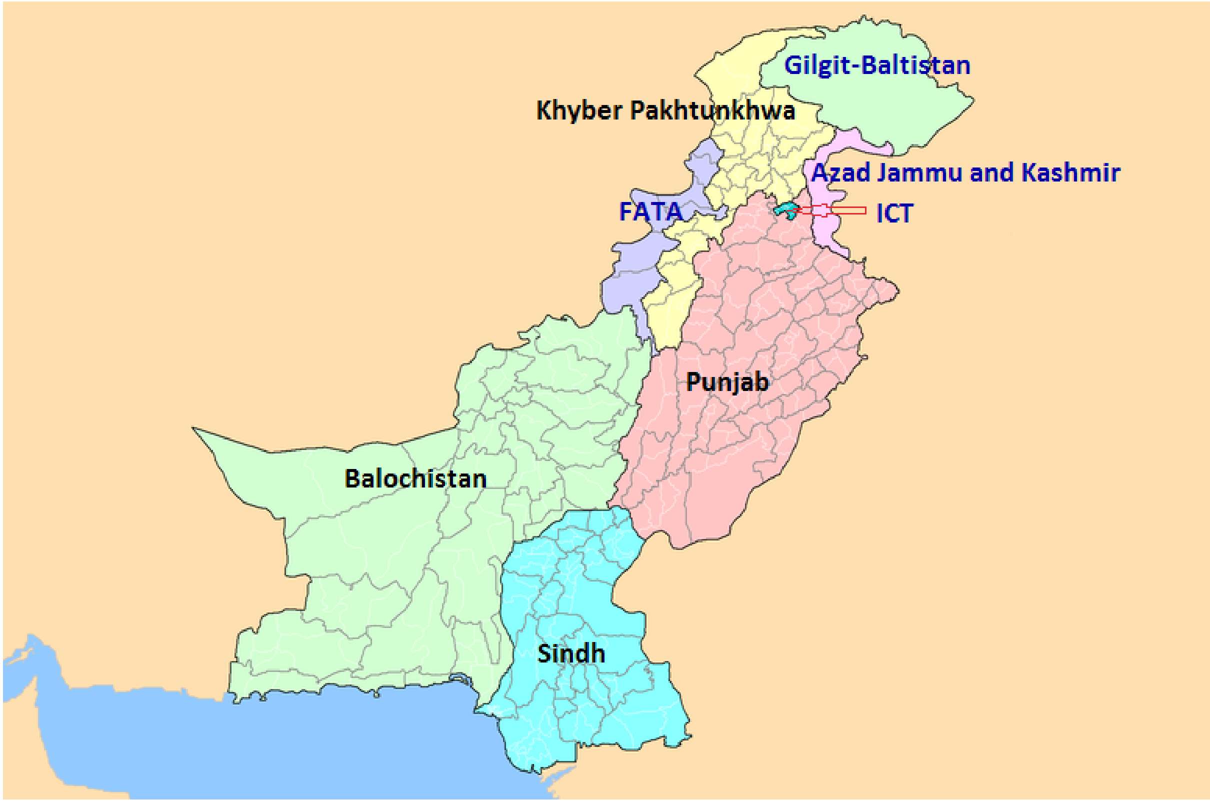


Figure 2: Histogram of in-migration rate (percent)

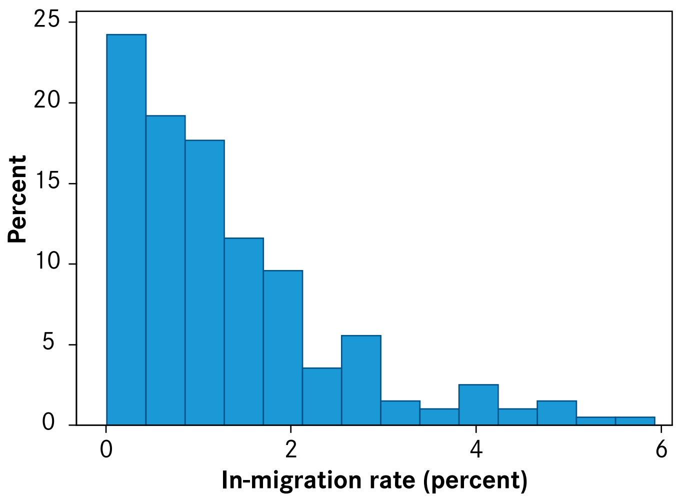


Figure 3: Histograms of revenue per hectare from major crops and wheat

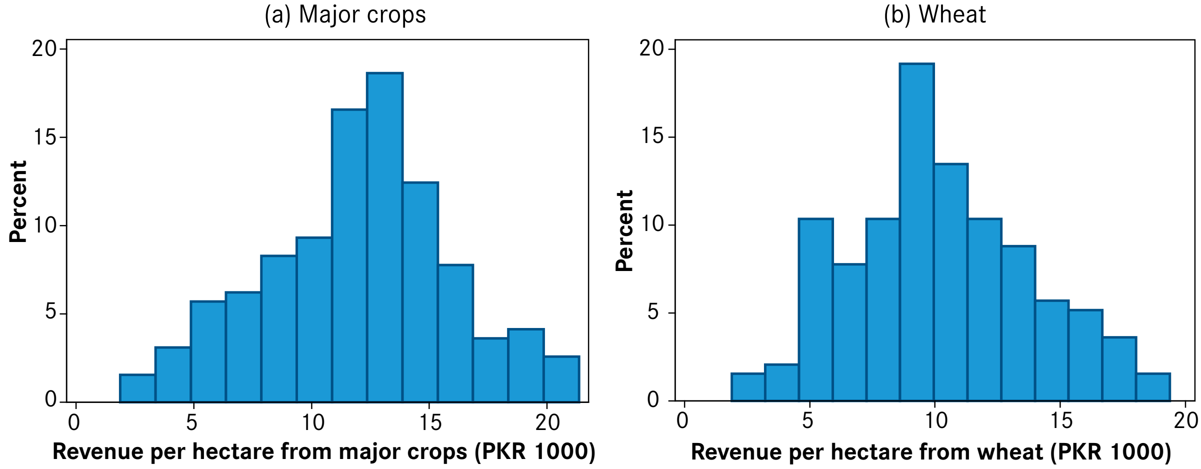


Figure 4: Histograms of temperature and precipitation: Annual and *Rabi* Season

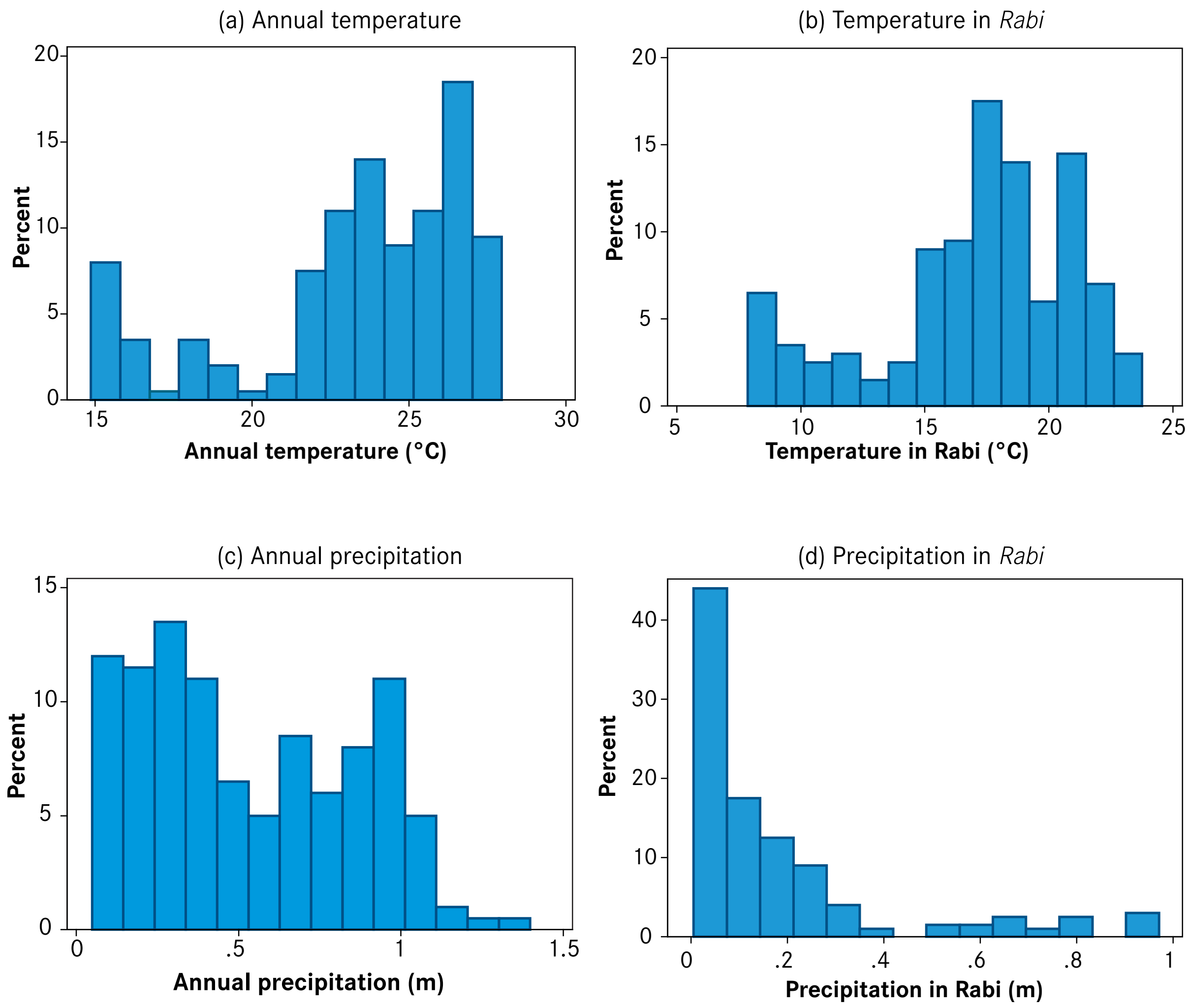
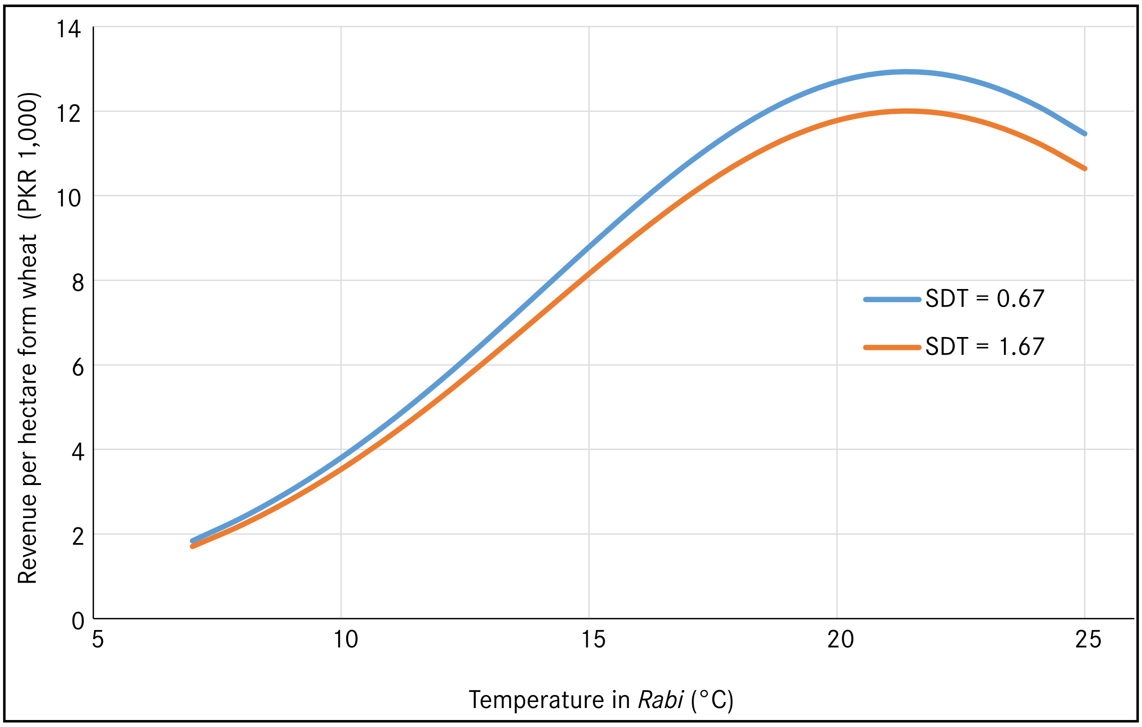
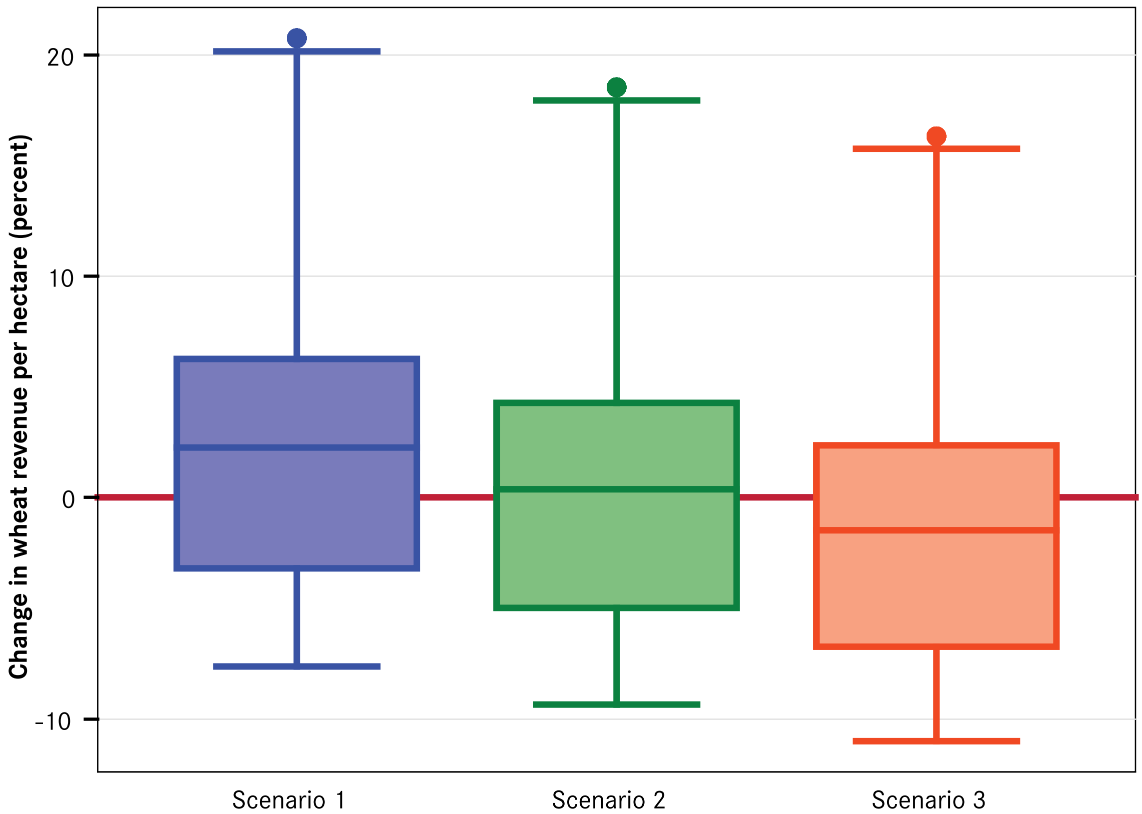


Figure 5: Fitted values of wheat revenue per hectare



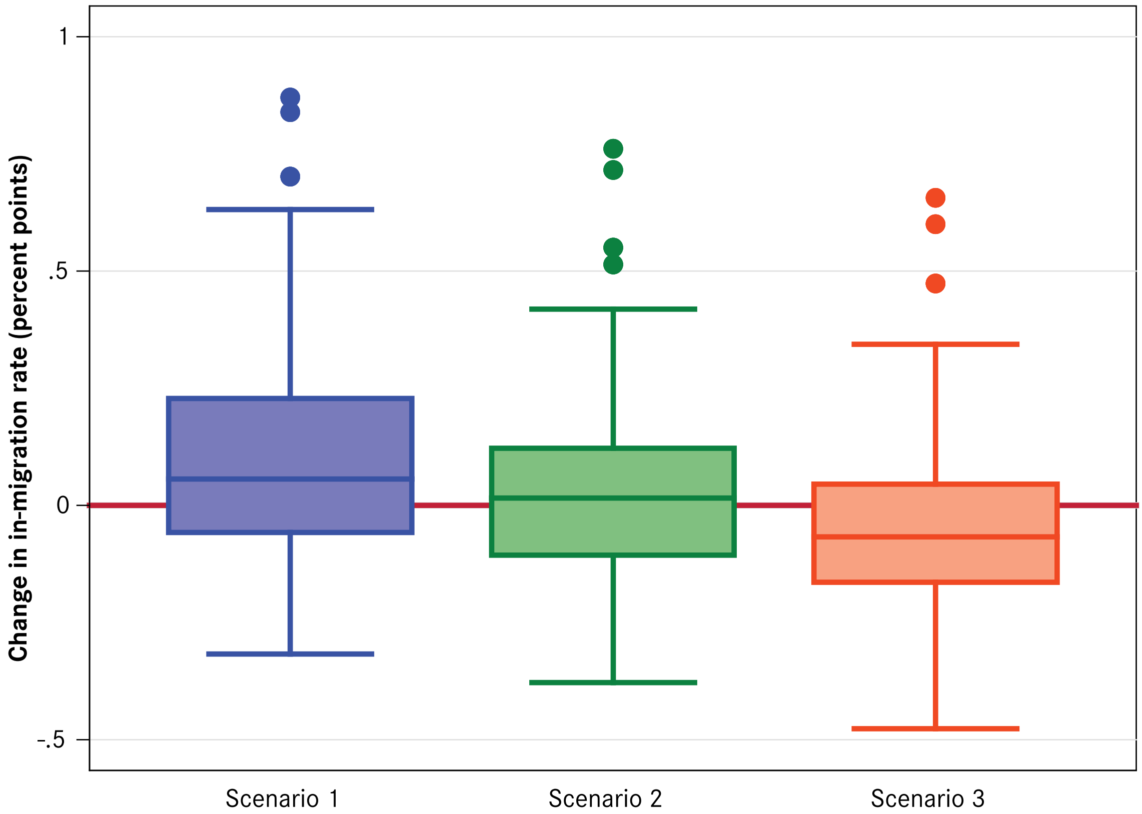
Note: SDT denotes standard deviation of temperature.

Figure 6: Projections of change in wheat revenue per hectare



Note: Projections are based on 1 °C increase in the average temperature in the *Rabi* season and 0.5, 0.75 and 1 °C increase in the standard deviation of temperature under scenarios 1, 2 and 3, respectively.

Figure 7: Projections of change in in-migration rate



Note: Projections are based on 1 °C increase in the average temperature in the *Rabi* season and 0.5, 0.75 and 1 °C increase in the standard deviation of temperature under scenarios 1, 2 and 3, respectively.

Figure 8: Projected change in in-migration rate in different districts versus temperature

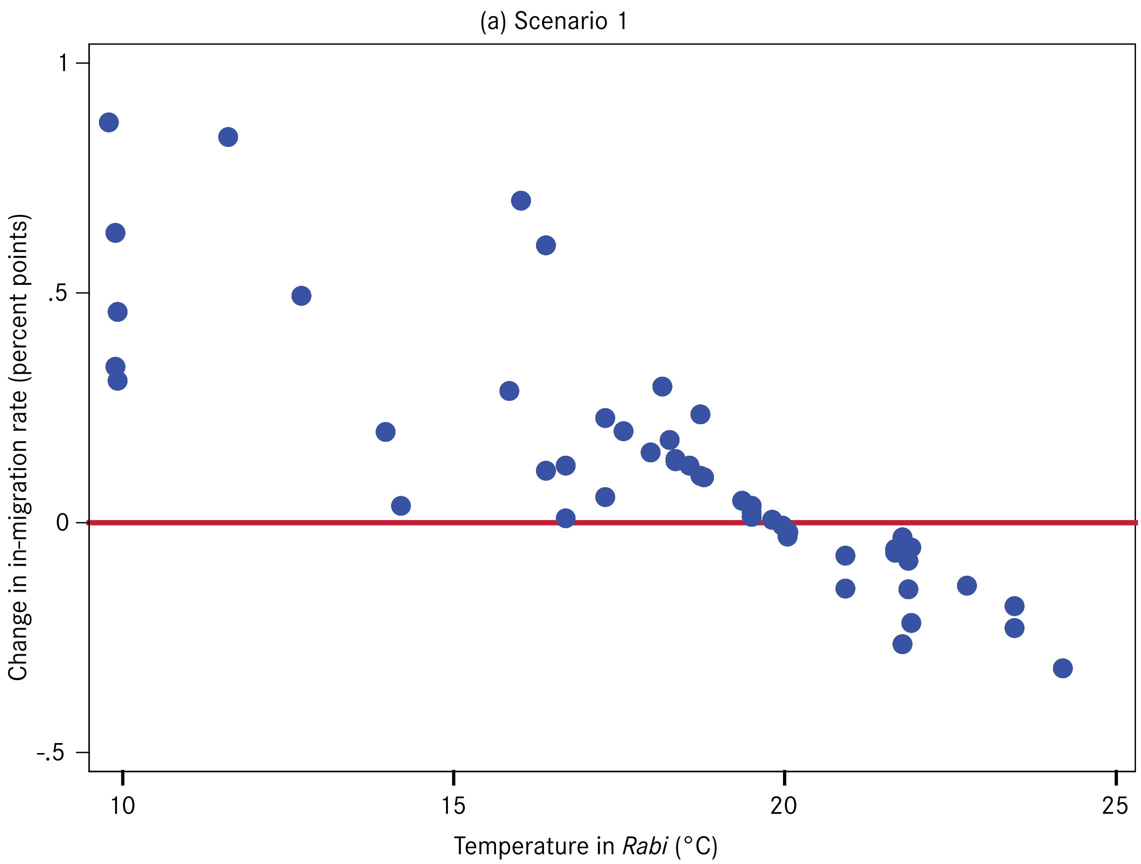
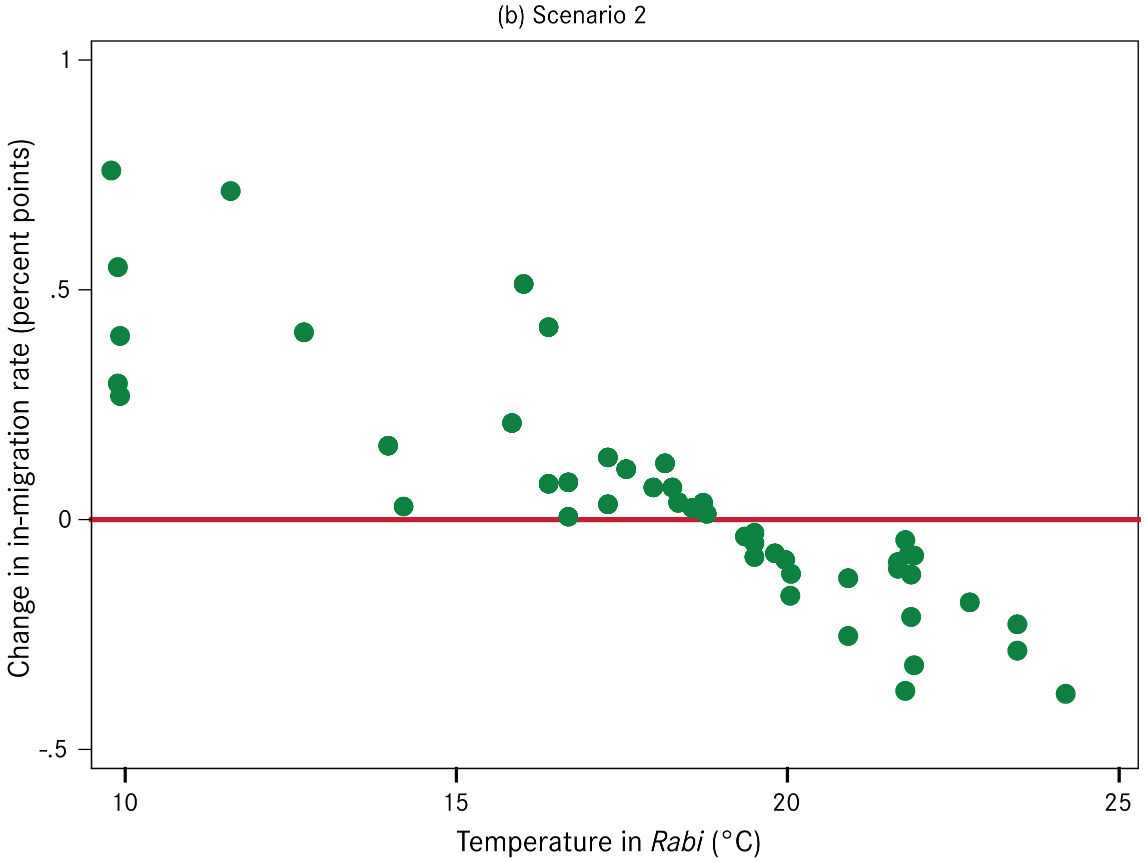
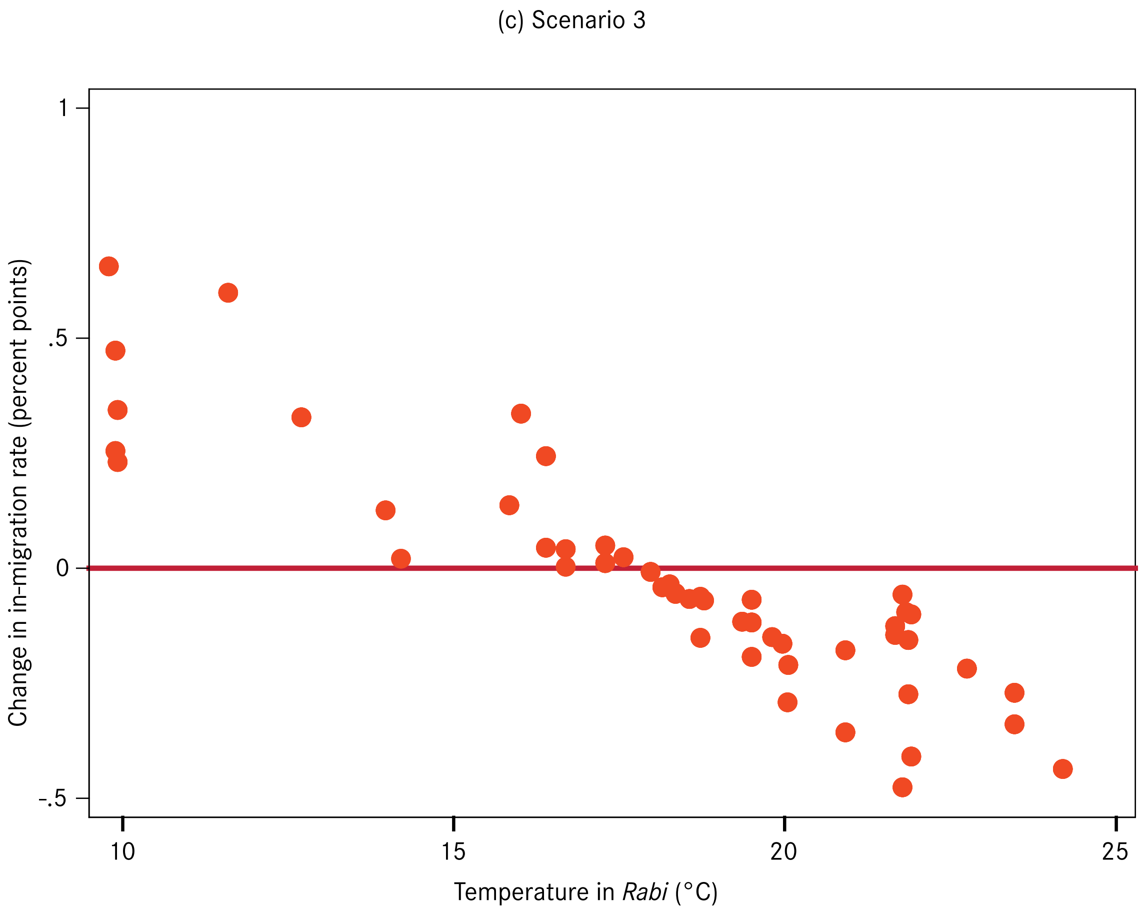


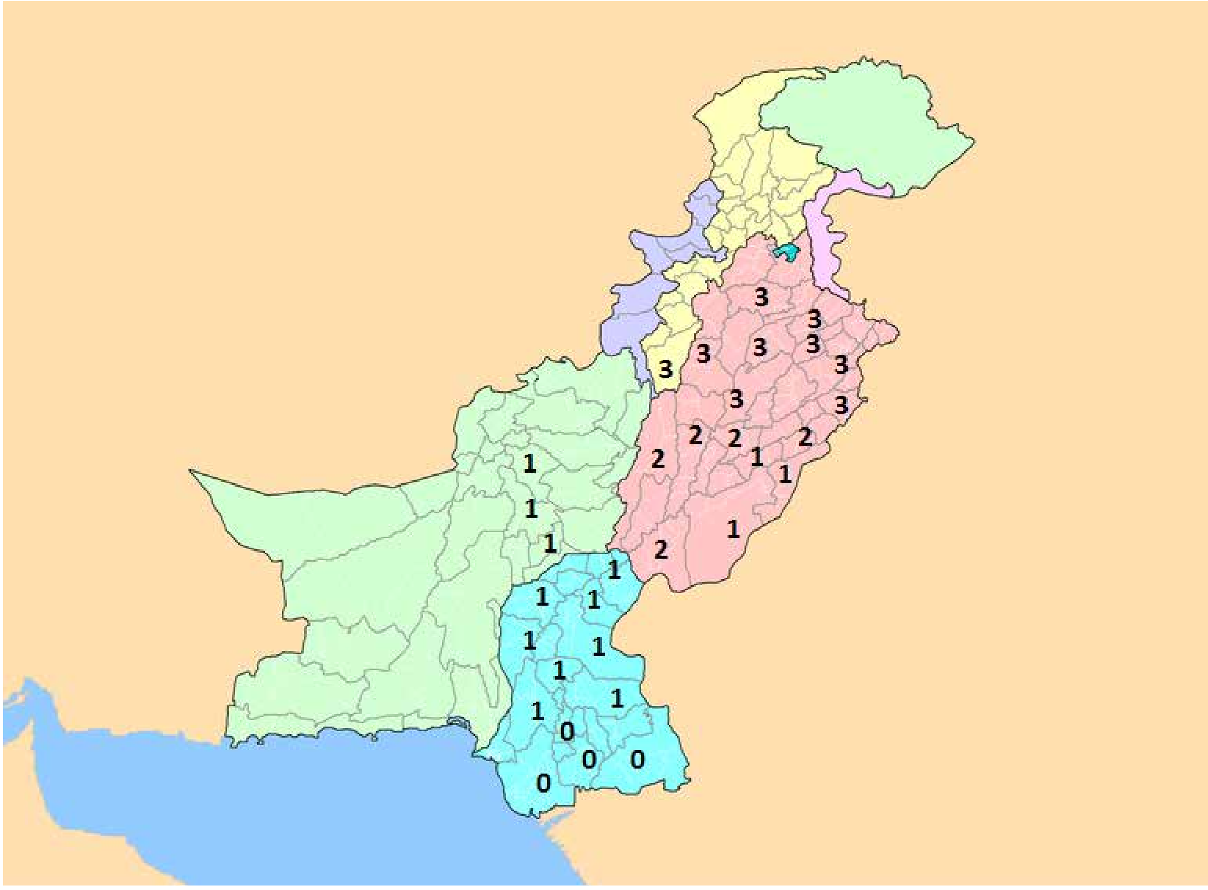
Figure 8: Projected change in in-migration rate in different districts versus temperature (cont.......)





Note: Projections are based on 1°C increase in the average temperature in the *Rabi* season and 0.5, 0.75 and 1°C increase in the standard deviation of temperature under scenarios 1, 2 and 3, respectively.

Figure 9: Map indicating districts adversely affected with predicted rise in temperature and its variability



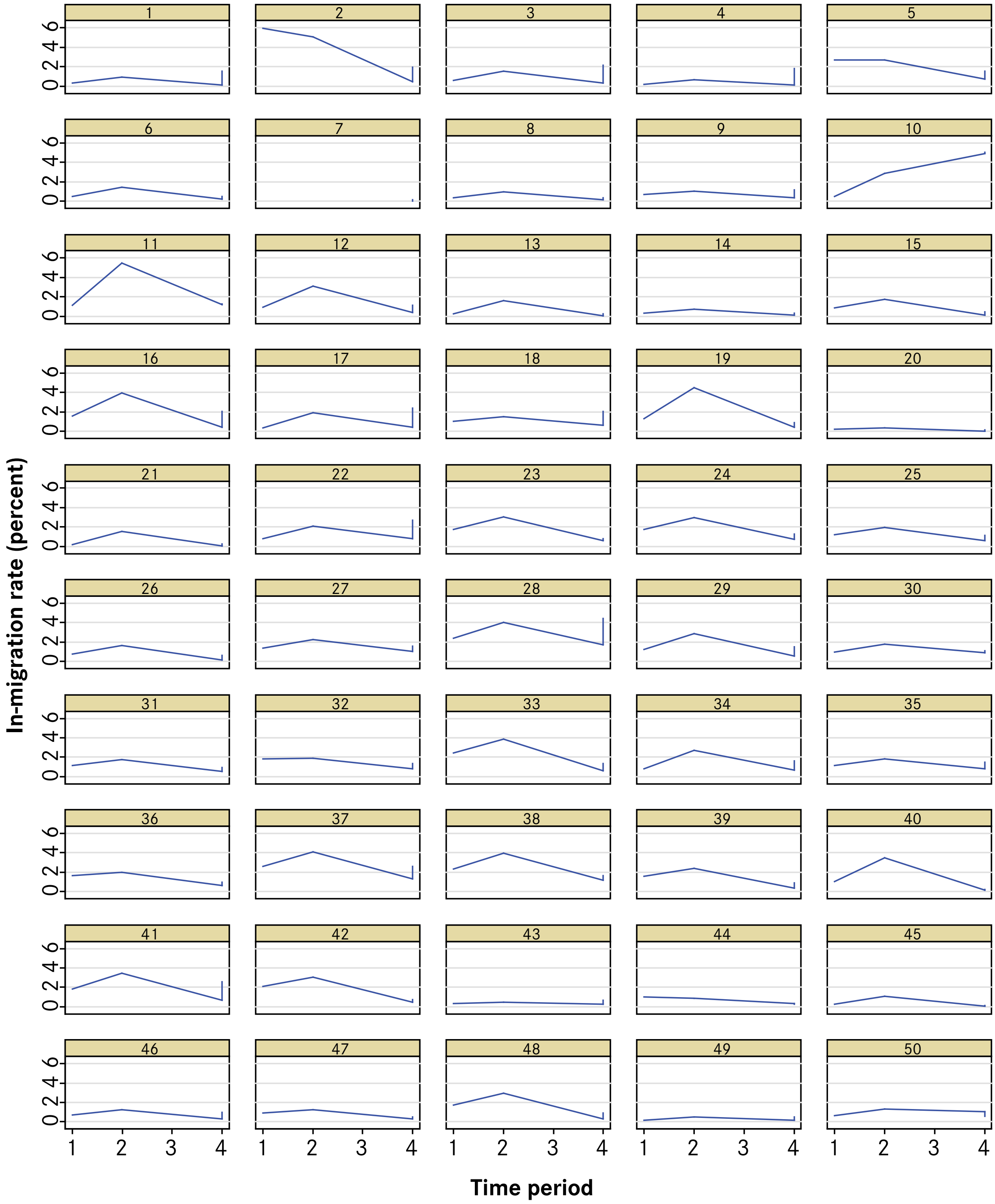
Notes: 0 indicates 4 districts (out of 50) that are already experiencing lower wheat yields than the optimum. 1 indicates additional 14 districts (total 18) projected to have reduced wheat revenue per hectare and in-migration rate under scenario 1. 2 indicates additional 5 districts (total 23) projected to have reduced wheat revenue per hectare and in-migration rate under scenario 2. 3 indicates additional 9 districts (total 32) projected to have reduced wheat revenue per hectare and in-migration rate under scenario 3.

Appendices

Appendix A: List of 50 districts or merged districts

District No.	District Name	District No.	District Name
Balochistan Province		*Sindh Province*	
1	Awaran & Khuzdar	39	Badin
2	Barkhan, Musakhel & Loralai	40	Dadu
3	Bolan & Kachhi	41	Ghotki & Sukkur
4	Dera Bugti & Kohlu	42	Hyderabad
5	Jafarabad & Nasirabad	43	Jacobabad
6	Kalat & Mastung	44	Khairpur
7	Kharan	45	Larkana
8	Kila Abdullah & Pishin	46	Tharparkar, Mirpurkhas, & Umerkot
9	Kila Saifullah & Zhob	47	Naushero Feroze & Nawabshah
10	Lasbela	48	Sanghar
11	Sibi & Ziarat	49	Shikarpur
Khyber Pakhtunkhwa Province		50	Thatta
12	Abbotabad & Haripur		
13	Bannu & Lakki Marwat		
14	Batagram & Mansehra		
15	Buner & Swat		
16	Malakand		
17	Swabi & Mardan		
18	D.I. Khan & Tank		
19	Hangu, Karak & Kohat		
20	Kokistan		
21	Dir		
Punjab Province			
22	Attock, Chakwal & Jhelum		
23	Bahawalnagar		
24	Bahawalpur		
25	Bhakkar & Mianwali		
26	DG Khan & Rajanpur		
27	Faisalabad, Jhang & Tobatek Singh		
28	Gujranwala & Hafizabad		
29	Gujrat & Mandi Bahauddin		
30	Kasur		
31	Khanewal, Lodhran & Multan		
32	Khushab & Sargodha		
33	Layyah & Muzzafargarh		
34	Narowal & Sialkot		
35	Okara, Pakpattan & Sahiwal		
36	Rahim Yar Khan		
37	Sheikhupura		
38	Vehari		

Appendix B: Overtime pattern of in-migration rate in each of 50 districts



Note: 1, 2, 3 and 4 denote time periods 1971–76, 1976–81, 1988–93 and 1993–98, respectively.

Appendix C: Reduced form regression results

Variables	Major crops	Wheat
Dependent Variable: Logit transformation of in-migration rate		
Constant	−13.351* (7.301)	−14.311*** (3.522)
Temperature	0.306 (0.597)	0.735** (0.358)
Temperature^2	0.003 (0.013)	−0.010 (0.010)
SD of Temperature	−0.157** (0.074)	−0.298*** (0.095)
Precipitation	0.588 (1.494)	7.171*** (2.049)
Precipitation^2	−0.067 (0.796)	−3.053** (1.435)
SD of Precipitation	−2.281 (4.432)	5.759 (12.464)
District FE and Time FE	Yes	Yes
Observations	191	191
R^2	0.840	0.851
F-statistics on temperature and its square [p-value]	4.39** [0.014]	5.02*** [0.008]
F-statistics on precipitation and its square [p-value]	0.20 [0.818]	6.13*** [0.003]
F-statistics on all weather variables [p-value]	3.17*** [0.006]	3.90*** [0.001]

Notes: *, ** and *** denote significance at 10%, 5% and 1%, respectively. HAC robust standard errors are in parentheses. Weather variables are annual measures for major crop and from Rabi season for wheat.

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