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Climate Change Induced Inter-Province Migration in Iran

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Abstract

We use Iran's national census data, covering the period 1996-2011, to empirically examine the existence and robustness of a relationship between inter-province migration and province-level climate, proxied by average levels of annual temperature and precipitation. Using a gravity equation and allowing for spatial correlation, we find that migration flows are significantly affected by both. This effect consistently persists over different specifications and implies that a rise in temperature and a drop in precipitation act as significant push factors. That (i) we focus our analyses on internal migration in a single county which excludes other major types of migration; (ii) the country has become increasingly vulnerable to climate change and has had a recent history of significant internal migration; and (iii) all the other relevant explanatory variables which are jointly included with climate variables turn out to have the expected impacts on migration flows, render our evidence robust and call for policy intervention.

Keywords: climate change; migration; gravity model; spatial correlation

JEL Classification: C21; N35; O15; Q54; R23

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Please contact the authors if you have any queries regarding our data source and/or the precise details estimation methods which are carried out using Stata software.

1. Introduction

The main aim of this paper is to understand if climate change plays a significant role in migration decisions once all other relevant factors have been accounted for. We focus on migrations induced by gradual changes in climate and do not consider displacements caused by sudden natural disasters. We also concentrate on a specific type of migration that does not involve crossing international borders; given that migration is costly, internal migration is likely to be the first resort for an average inhabitant who decides to move away in order to overcome the adverse effects of a deteriorating habitat. We therefore select the country in question ensuring that it has a history of sufficient population mobility and also shows symptoms of gradual climate change. Iran satisfies both these requirements and, in addition, has a regular population census and province-level socio-economic data which can be used to construct a dataset that consists of at least two recent waves of migration flows. We compile a dataset based on the 1996-2011 period and use it to carry out an econometric analysis of the relationship between bilateral inter-province migration flows, province-level socio-economic variables which are commonly considered as determinants of migration decisions, geographical profile, and two main indicators of climate change: average annual temperature and precipitation levels. Our findings suggest that people do tend to leave regions which are becoming warmer and that a rise in precipitation in general dampens migration flows. Our results signal worthwhile policy implications.

The rest of the paper is organised as follows: Section 2 highlights the relevance of our analysis in the context of the literature; Section 3 briefly explains the ingredients of our dataset; Section 4 outlines the theoretical underpinning of the specification of the model we use and presents and discusses the resulting econometric evidence; Section 5 concludes the paper.

2. Motivation and background

Migration is a costly process but can be induced by a number of factors amongst which economic opportunities, civil and international conflicts, religious and ethnic clashes, and climate change feature as most common (UNEP, 2012). Climate-induced migration has received more attention in recent years as the importance of understanding the impacts of climate change and the consequences of steady migration flows have stimulated policy debates internationally. One of the early studies, carried out for an Intergovernmental Panel on Climate Change assessment report (IPCC, 1990), identified human migration as the greatest single impact of climate change. This was followed by concerns raised in International Organization for Migration (IOM, 1992) regarding the dramatic increase in mass displacements and the anticipation of substantial rise in forced migration flows as climate change made large areas in different parts of the world uninhabitable. Since then, however, the number of natural disasters has more than doubled: according to reports by the Internal Displacement Monitoring Centre (IDMC) and the United Nations Office for the Coordination of Humanitarian Affairs (OCHA), in 2008 more than 20 million people were displaced by sudden onset of climate related natural disasters and extreme weather events, compared to 4.6 million displaced over the same period by conflict and violence – some of which, incidentally, could have been provoked by climate change (OCHA-IDMC, 2009). Publically available projections suggest that the number of individuals displaced due to climate change – i.e. the number of so called environmental migrants[1] – will rise substantially, to an estimated figure of 200 million people by 2050 (Gemenne et al., 2012).

Whilst significant sudden displacements that are caused by severe and abrupt changes in climate conditions are reported and discussed widely (Meerow and Mitchell, 2017, highlight some of the issues and discuss in some detail the importance of adaptation strategies especially in urban settlements), less attention is devoted to the impact of steady changes in climate which are long known to induce gradual and slow migration flows by affecting the habitability of living environments. However, if unrestrained, this more subtle but persistent form of displacement is likely to have severe long term socio-economic as well as environmental consequences: there are various examples of how this type of migration might lead to a vicious circle of civil conflict and poverty associated with overcrowding of urban centres and desertification of the rural regions.[2]

Despite the fact that the impact of climate change is likely to be spread globally eventually, certain regions and/or countries will inevitably be more severely affected initially. Amongst these are regions that are more prone to climate change – due to, e.g., low geographical altitude, etc. – and/or the less developed and relatively poor countries with weak infrastructure and inability to respond quickly (IPCC, 1997). For instance, given the high level of water scarcity in MENA (Middle East and North Africa region) and the fact that a significant source of its inhabitants' livelihood is directly and inflexibly reliant on more conventional water-dependent agriculture, the region is considered to be highly vulnerable to climate change in the coming decades.[3] Given the scale and importance of the problems involved in such cases, there are surprisingly few statistical studies of the phenomenon which attempt to quantify the contribution of climate change to migration flows and to predict the impact of gradual change in climate, especially in more sensitive regions like MENA.

A glance through the existing literature reveals that most statistical studies of migration flows focus on its socio-economic determinants and do not specifically examine the role of climate factors. Amongst recent examples of such studies, Mayda (2010) and Ruyssen et al.

[1] Environmental migrants are defined as "*persons or groups of persons who, for compelling reasons of sudden or progressive change in the environment that adversely affects their lives or living conditions, are obliged to leave their habitual homes, or choose to do so, either temporarily or permanently, and who move either within their country or abroad*" (UNEP, 2012).

[2] Opitz-Stapleton et al. (2017) and Beyani (2014), amongst others, discuss in some detail the unavoidable consequences of forced migration and analyse the likelihood that they are caused by climate change. In a 2010 IOM and Gallup World Poll (Esipova et al., 2011), almost 12% of respondents believed severe environmental problems would require them to move within the next five years.

[3] The part in MENA which covers eastern Syria and Turkey, northern Iraq and western Iran entered a three-year drought period in 2007 – the worst since records started – which drove a large rural population to cities, which in turn is known to have triggered some of the problems the region has experienced since. See World Bank (2014a), Brown and Crawford (2009) and Kelley et al. (2015) for details.

(2014) examine migration flows to specific OECD countries, mainly from other countries, and find income opportunities in the destination country to play a significant role as '*pull factor*'. Ruyssen and Rayp (2014) study the determinants of intraregional migration in sub-Saharan Africa and come to the same conclusion within an extended human capital framework. In a similar vein, Mulder and Malmberg (2014) find that family ties reduce the likelihood of migrating for Swedish couples. Stillwell et al. (2016) focus on the spatial features of internal migration and find that mean migration distances are positively associated with income but vary across countries with different size and population density.

Those studies that examine the role of climate are either case-study based – see Warner et al. (2009) for an evaluation of such studies in general, and Hassani-Mahmooei and Parris (2012), Joseph and Wodon (2013) and Ow et al. (2015) for a study of the situation in Bangladesh, Yemen and Malaysia, respectively, as recent examples – or predominantly focus on natural disasters and extreme events – see Belasen and Polachek (2013) for an overview of these studies. Afifi and Warner (2008), Beine and Parsons (2013) and Backhaus et al. (2015) are amongst the very few studies which carry out econometric analysis of the relationship between *bilateral migration flows* and *climate factors* as well as other determinants.[4] These studies estimate regression equations which are specified on the basis of the *gravity principle* and therefore enable identifying which determinants act as '*push factor*' as opposed to '*pull factor*'. They all focus on cross border migration and use data from international migration statistics, e.g. OECD's International Migration Database, and analyse flows of population between a large number of countries or to a limited number of OECD host countries. Their findings with respect to the role of climate change, however, are on the whole inconclusive. Afifi and Warner (2008) use the cross country migration data for 226 origin/destination countries for year 2000 only, provided by the Development Research Centre on Migration, Globalisation, and Poverty. Amongst the explanatory variables they use there are 13 which one way or another represent some type of climatic effect. Their results suggest that on the whole the latter play a significant role in inducing emigration. However, given their wide range of the environmental variables – all of which appear in 0/1 dummy form[5] – and the fact that they cannot account for any country-specific unobservable effects, it is not possible to ascertain from their results how climate change in particular, or environmental factors in general, affect migration. Beine and Parsons (2013), on the other hand, use bilateral migration flows corresponding to 137 origin and 166 destination countries over 5 decade-based census rounds covering the 1960-2000 period but do not find any evidence that climate change factors

[4] For other statistical analysis of migration flows that consider the role of climate factors, see Naudé (2009), Reuveny and Moore (2009), Andersen et al. (2010), Joseph and Wodon (2013), Joseph et al. (2014) and Hassani-Mahmooei and Parris (2012) amongst others. While these studies reveal valuable information about the role of climate, the specification of their regression models and measurement of migration flows differ from the gravity-based models which consider pairwise flows.

[5] These dummies are for the occurrence in the sending country of 'over-fishing', 'earthquakes', 'tsunamis', 'floods', 'hurricanes', 'desertification', 'lack of potable water', 'soil salinity', 'deforestation', 'sea level rise', 'air pollution', 'soil erosion', and 'soil pollution'.

significantly induce international migration.[6] One explanation they offer for this finding is that "*If liquidity constraints are binding, internal migration to less affected areas within the same country is a valuable option.*" This is consistent with the evidence reported in Beyani (2014) that, due to the cost of relocation and benefits of community networks in familiar and nearby locations, most of the displacements caused by climate change primarily take place within national borders. Backhaus et al. (2015) use a sample of 142 origin and 19 OECD destination countries over the 1995-2006 period. Their emphasis is on capturing the effect of gradual climate change which they measure using variations in annual weighted averages of temperature and precipitation, and their results support the hypothesis that gradual climate change induces emigration. They also state that their "*preliminary examination of potential channels suggests that the reaction of migration due to temperature changes may in particular be driven by a sending country's agricultural dependence*."

The above background suggests that a clearer picture might emerge if the empirical study focused on examining the determinants of internal migration within a single country with a history of population mobility and with a varied climate and a relatively significant agriculture-dependent rural habitation, but one whose climate has been undergoing a gradual change. A sample of inter-province migration (which is not subject to the prohibitive costs associated with international migration and excludes other migration types such as politically induced ones which internal migration cannot resolve) constructed over a sufficiently long period of time (to allow for some climate change) for such a country would reduce measurement problems and enable a sharper distinction of the role of climate change. We have chosen to study Iran as an example of such country.

3. Data

3.1. *Why Iran*?

Iran satisfies the requirements specified above. Its physical geography features predispose it to consequences of climate change: more than 80% of its area is arid or semi-arid, with around 20% desert coverage and only 9% of the country's 1.648 million km² area is forest land (Iran's National Climate Change Office, NCCO, 2010); the shares of arable and agricultural areas, which were respectively 10.1% and 39.2% in 1996, had already reduced to 9.3% and 28.5% by 2011.[7] In comparison with global averages, parts of the country severely lack in rainfall; its annual average precipitation was 203mm, compared to 1121mm globally, in the 1996-2011 period.[8] The World Resources Institute ranks Iran amongst top water-stressed countries (Luo

[6] The variable representing natural disasters is measured by the total number of occurrences in each decade of 'droughts', 'earthquakes', 'extreme temperatures', 'floods', 'storms', 'volcanic eruptions', 'epidemics', 'insect infestations' and 'other miscellaneous occurrences'. Gradual variations in climate are captured by (anomalies in) temperature and precipitation fluctuations over each decade.
[7] Data are from the Statistical Centre of Iran (SCI) and the years correspond to the initial and final years in our sample period.
[8] The source is World Bank (2014b), based on 173 countries for the same period.

et al., 2015) and its projections suggest that a 3ºC increase in temperature would reduce Iran's crop yields by 30% (WRI, 2013). Gohari et al. (2013) predict that climate change is likely to lead to a significant reduction in Iran's four major crops – wheat, barley, rice, and corn – in the next three decades. The country has already experienced multiple episodes of unprecedented sand storms in the western parts and some of the major rivers and lakes have either dried up or are receding. Figure 1 below shows the share of rural population in each province. Together with Figure 2, which is constructed under the collaborative project between NCCO and the United Nations Development Programme, it illustrates that on the whole areas with higher shares of rural population are likely to experience a bigger drop in precipitation level.

Figure 1. Share of province-level rural population (SCI, 2015)

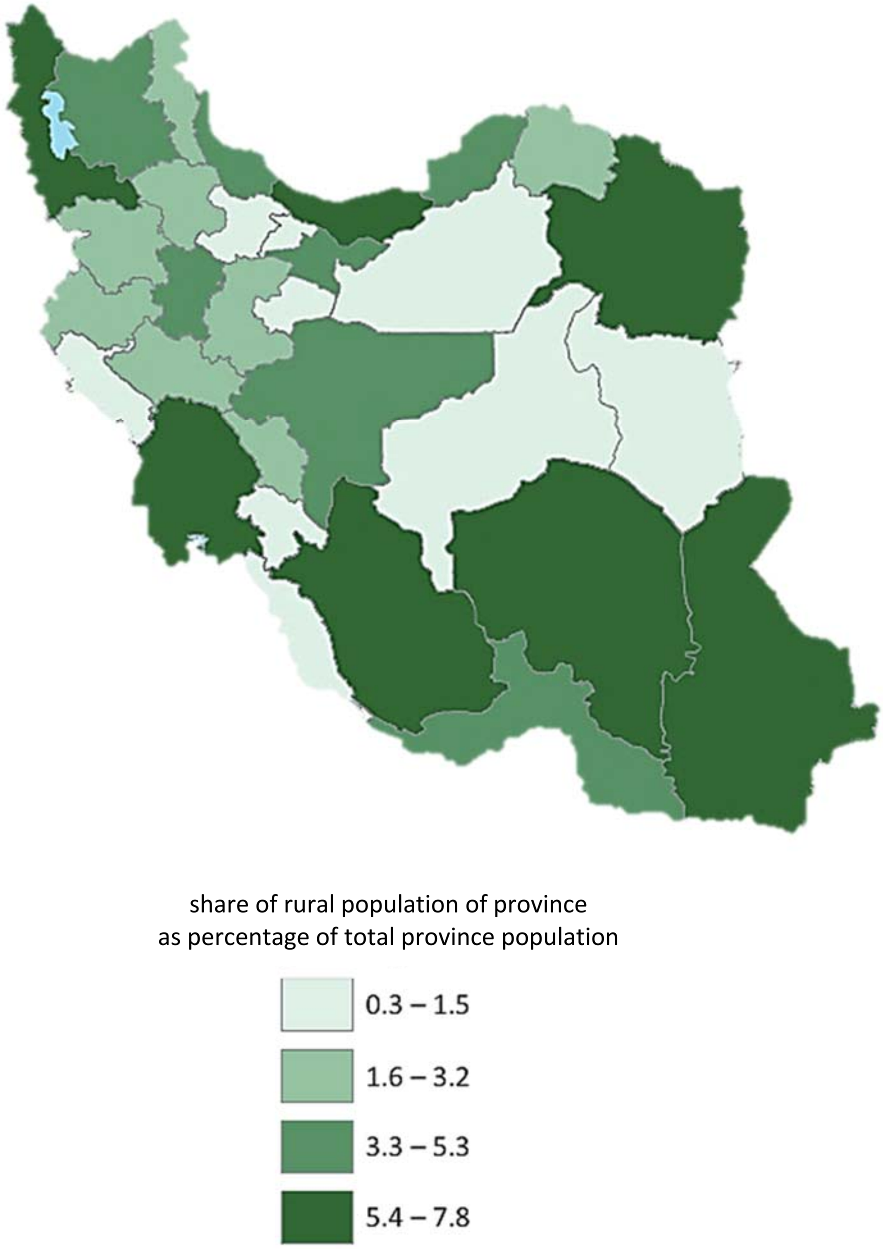
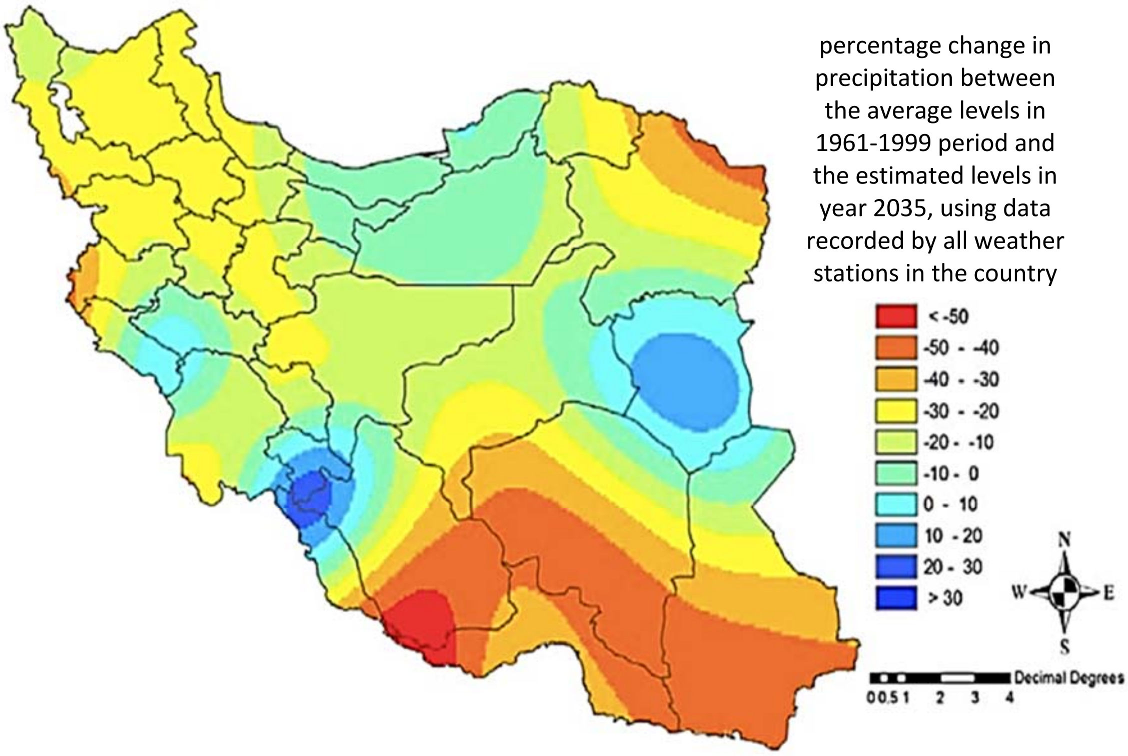


Figure 2. Projection of change in precipitation levels (NCCO, 2015)



While environmental concerns might become one of the main factors underlying internal migration decisions, population mobility within the country per se is not a new phenomenon. A major episode of internal migration occurred over a century ago when the country went through fundamental changes following the discovery of major oil fields. The resulting economic growth transformed the main cities into centres of economic activity and led to the first major waves of rural-to-urban migration. The major Land Reform Act, launched in 1963 by the late Shah of Iran, and the OPEC induced oil boom of the early 1970s further boosted this pattern (Taleb and Anbari, 2005), albeit for different reasons. Finally, the 1979 revolution followed by the 1980-1988 Iran-Iraq war substantially contributed to migration trends. Consequently, of the total population of about 75 million people in 2011 (SCI, 2011), 71% was settled in urban areas and this number is expected to reach 80% by 2050 (Mahmoudian and Ghassemi-Ardahaee, 2014). Demographic data suggest that over the last three decades on average one million people per annum have moved within the borders of the country, and that over the 1996-2011 period there has been a 5% decrease in the rural population where the country has experienced a downward trend in the total number of rural villages.[9] Stillwell et al. (2016) examine a migrant-weighted measure of distance travelled by internal migrants over 5-year census period (*MMD*), within a sample of 19 countries that include Iran. They find that

[9] The official figures for the number of villages in 1996, 2006 and 2011 are, respectively: 68122 (234), 63125 (207) and 61748 (209) where the numbers in parentheses are villages with 5000 or more inhabitants.

internal migration in Iran exhibits a more even distribution of flows between pairs of '*basic spatial units*' (*BSU*). In addition, by examining the shape of the curve which maps a country's *MMD*s to its number of aggregated *BSU*s, they find that scale effects on *MMD* are most apparent in Iran, along with Brazil, Canada and Mexico; after the US, these four countries are found to have the highest average migration distance (of around 200km).

The above characteristics, namely the severe environmental impacts of climate change and the dynamic nature of its migration, as well as the fact that Iran still has a substantial agriculture-dependent rural population, make the country an interesting case study for understanding the role of climate change in determining migration.

3.2. *Variables of interest*

We use the information on individual characteristics provided by the Iranian National Census data to construct our migration flow matrix. Until 2006, nationwide censuses used to take place every ten years and since then their frequency has been reduced to every five years. Our sample is constructed using the pooled cross-section data from the two consecutive censuses respectively covering 21 March 1996 to 20 March 2006 and 21 March 2006 to 20 March 2011 (the Iranian calendar starts on 21 March). We exclude the earlier censuses because there is a lack data on most variables of interest for those years, and also a major province reform was implemented during the 1988-1996 period which affected the geographical boundaries.[10] We use the standard definition of a migrant as an individual who has changed her/his place of residence during the census period and concentrate our analysis on internal migration, only considering inter-province movements within the country.[11] Our dataset includes all 30 provinces with $870\ (= 30 \times 30 - 30)$ origin-destination inter-provincial flows for each census period which exclude intra-province relocations.

Given that the first census covers a larger number of years than the second, we use the average annual number of migrants in each census – recorded under *immigration*, instead of *emigration*[12]. Figure 3 compares the average annual number of migrants leaving each province over the two censuses. The fact that the numbers during the more recent census period are lower can be explained by noting that (i) the earlier census covers the years of adjustment that followed the Iran-Iraq war, and part of the movement in population could therefore be

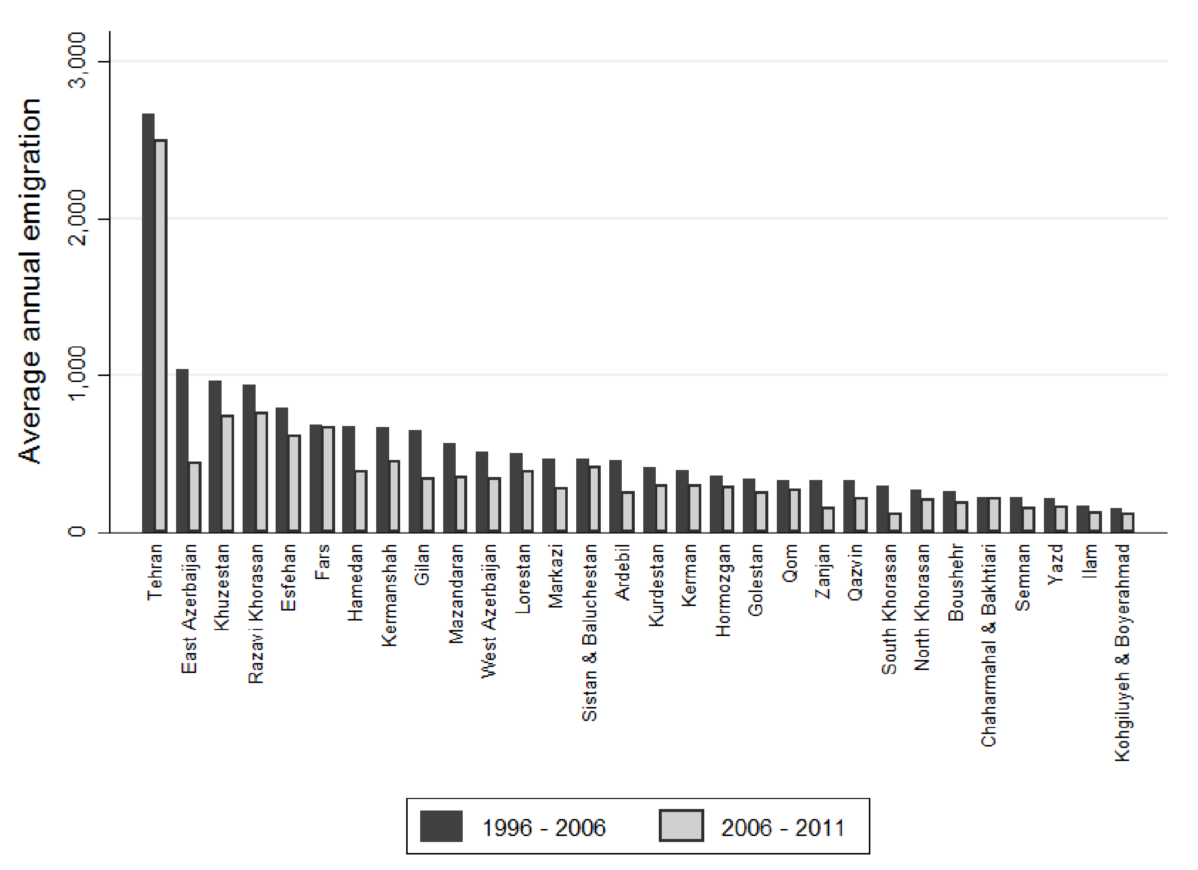
[10] The *Alborz* province was created in 2010 by dividing the *Tehran* province and is treated as part of the latter in our analysis, i.e. all movements to and from *Alborz* are added to those of *Tehran's* and movements between *Alborz* and *Tehran* are considered as intra-province movements and therefore omitted. Other provinces created as a result of the above-mentioned reforms are *Golestan* (separated in 1996 from *Mazandaran*), *Qazvin* (separated from *Tehran* in 1996), and *North, Razavi* and *South Khorasans* which were created in 2004 by dividing the original *Khorasan* province.

[11] Inter-district migration would have been preferable but data at the district level are not available for all relevant variables.

[12] In a closed system with accurate data, the number of immigrants in a province A who are originally from another province B in a given period should be equal to the number of emigrants from B who have moved to A within the same period. However, in practice there is always a difference due to errors in reposting, recording, etc. We have chosen to work with immigration records simply because emigration-based responses were found to be less accurate due to a larger number of un-stated responses.

accounted for by relocation of those displaced during the war year; (ii) the earlier period also coincided with post-war reconstruction years as well as the 1993-2001 interval which saw implementation of the industrial development policy that stimulated waves of migrants attracted by the new opportunities that the targeted cities presented; and (iii) in more recent years the on-going infrastructure improvement policies were increasingly directed towards the less developed regions which reduced the outflow of migrants from those parts.

Figure 3. Number of emigrants by province and census period



We use, as determinants of bilateral migration flows, a set of explanatory variables that includes those commonly used in the existing studies and capture the impact of gravity factors, economic and welfare opportunities, and environment and climate features. Table 1 provides the details where, with the exception of *distance* and *area* (denoted by D and A respectively), which are time invariant, all variables vary across provinces and over time.

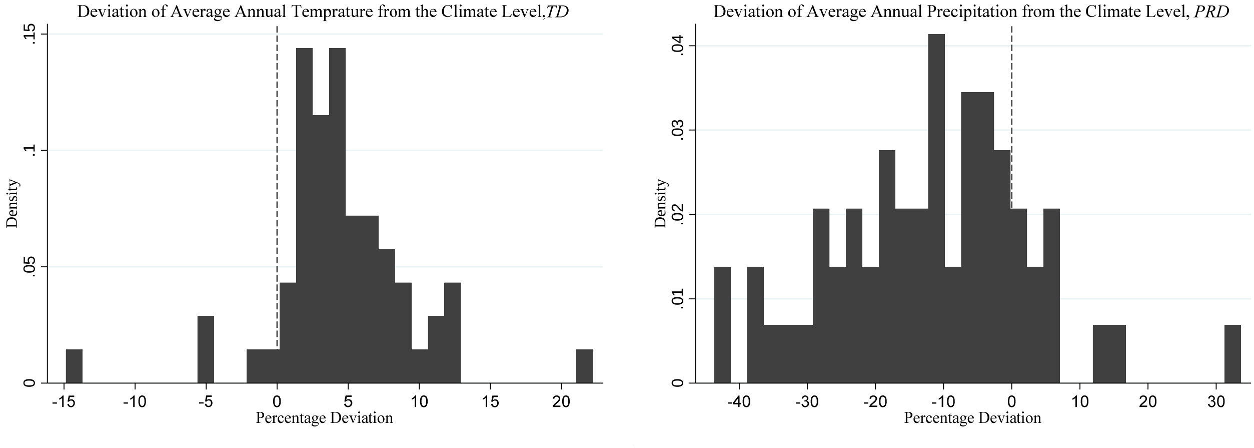
Given our focus on the impact of climatic variables, in Figure 4 we illustrate deviation in temperature and precipitation (across all provinces) from their climate levels which indicate that the country as a whole has experienced both a warming up and a drying up trend over the 1996-2011 period.

Table 1. List and definition of the variables used in the regression analysis

Notation	Definition
$\boldsymbol{M_{ij}}$	number of people leaving the origin province *i* for destination province *j* (the dependent variable)
$\boldsymbol{D_{ij}}$	driving distance, in km, between the capital cities of the origin province *i* and the destination province *j*
$\boldsymbol{A_p}$	total area in square km of province p
$\boldsymbol{P_p}$	total population of province p
$\boldsymbol{Y_p}$	real GDP of province p in constant 2003 prices (millions of Iranian rials)
$\boldsymbol{G_p}$	growth rate of real income in province p
$\boldsymbol{GINI_p}$	income-based Gini index of province p
$\boldsymbol{INF_p}$	inflation rate of province p
$\boldsymbol{UR_p}$	share of the unemployed in working age population of province p
$\boldsymbol{ER_p}$	share of educated population of province p (as % of the over 5 year old population)
$\boldsymbol{RPS_p}$	share of rural population of province p (as % of total province population)
$\boldsymbol{RHD_p}$	number of rural health centres per 10000 rural province population
$\boldsymbol{HPD_p}$	number of health professionals of province p per 10000 province population
$\boldsymbol{RR_p}$	share of the area of province p covered with rangeland (as % of total province area)
$\boldsymbol{RD_p}$	share of desert area of province p (as % of total province area)
$\boldsymbol{T_p}$	average annual temperature of capital city of province p (in Celsius)
$\boldsymbol{TD_p}$	deviation of province p temperature form its climate level (as % of the climate level)
$\boldsymbol{PR_p}$	total annual precipitation of province p in mm
$\boldsymbol{PRD_p}$	deviation of province p precipitation form its climate level (as % of the climate level)

- Unless otherwise stated, all variables are measured as annual averages over the census period; midpoint averages were used in cases where annual observations over the census period were unavailable.
- The raw data on climatic variables were obtained from the Iranian National Climate Change Office.
- T_p is the mean over the census period of the average daily temperature of province's capital city, i.e. (maximum daily temperature + minimum daily temperature)/2. $TD_p = (T_p - CT_p)/CT_p$ where CT_p is the moving average of T_p of over the last 30 years.
- PR_p is the mean over the census period of the total precipitation for each province's capital city for each year. $PRD_p = (PR_p - CPR_p)/CPR_p$ where CPR_p is the moving average of PR_p of over the last 30 years.

Figure 4. Climate change over the sample period



4. Empirical methodology and evidence

We use the gravity principle to determine the specification of our model. Such specifications are commonly used to capture spatial interactions where the dependent variable measures some pairwise flows between any two locations in the sample. In particular, they have been widely applied by economists, regional scientists, demographers and human geographers to explain bilateral flows of goods, services, investment, population, or even spread of disease.[13] Below, we first outline the model and then present and discuss the results based on estimating its parameters.

4.1. *The regression equation*

A gravity equation explains pairwise flows between different locations. In its basic form, it is postulated that the amount of bilateral flow M_{ij} – e.g. the number of migrants – between any two locations i and j, $i \neq j$, is determined by the distance D_{ij} between them and some measure representing the so called 'mass' or 'size' of each location. Denoting the latter by W, the underlying equation is

$$M_{ij} = D_{ij}^{\delta} W_i W_j, \quad i \neq j = 1,2, \dots, N, \tag{1}$$

where δ is a constant parameter; if D and W are accurate measures it is expected that $\delta = -2$ as in the original gravity equation. As mentioned above, we approximate D by the driving distance between the capital cities of the two provinces. As for W, we assume it is a composite measure defined by a weighted basket of variables that reflect the importance and/or attractiveness of a location. In particular, we let

$$W_p = e^{(z_p' \beta_p + c_p' \gamma_p)}, \quad p = i, j, \tag{2}$$

where e is the natural base and z and c are vectors whose elements are the appropriate transformations of variables listed in Table 1: z includes $A, P, Y, GINI, G, INF, UR, ER, RPS,$ RHD, HPD, RR and RD while c comprises either T and PR or TD and PRD; β_p and γ_p are the corresponding vectors of parameters representing the weights attached to elements of z and c. Substituting from (2) into (1) to eliminate W_p, using the log-linear version of the resulting equation and augmenting it with a constant intercept, province and census fixed effects respectively denoted by θ, ω and τ, the corresponding general linear regression model therefore is,

$$\ln M_{ij,t} = \theta + \delta \ln D_{ij} + z'_{i,t}\beta_i + z'_{j,t}\beta_j + c'_{i,t}\gamma_i + c'_{j,t}\gamma_j + \omega_i + \tau_t + u_{ij,t}, \tag{3}$$

where the subscript $t = 1,2$ refers to the two consecutive censuses and $u_{ij,t}$ is the random disturbance term of the regression which reflects all the omitted effects. It is therefore assumed

[13] See Head and Mayer (2013) for a recent review of the formulation and estimation of gravity equations and Backhaus et al. (2015), Barrios et al. (2012), Beine et al. (2015), Greenwood (2005) and Lowry (1966), for examples of applications. Bailey and Gatrell (1995) provide an in depth analysis of modelling spatial data.

that $E\left[u_{ij,t}\right] = 0$ holds for all i, j and t. Also, since observations correspond to averages over census periods, $E\left[u_{ij,1}\, u_{ij,2}\right] = 0$ could be assumed to hold for all i and j. However, $E[u_{ij,t}\, u_{ji,t}] \neq 0$ cannot be ruled out for each $t = 1,2$, since the reasons that a large number of people move from one province to another during a given period could be highly correlated with the reasons why a small number of people move in the opposite direction during the same period. Therefore, while under these assumptions the OLS estimates of the parameters are consistent, we need to use standard errors which are clustered at province level in order to take account of correlated errors within pairs.

In addition to exploring the OLS estimates of the above model, we shall also examine estimates based on generalisations which allow for the possibility of spatial interactions that could be responsible for the above mentioned heteroscedasticity. To see this, we write the regression equation (3), which is in practice a 3-dimensional panel equation, in the matrix form

$$F_t = X_t\phi + \mu + U_t, \tag{4}$$

where, for each t, F_t is the $N(N-1)$ vector of all pairwise $\ln M_{ij}, i \neq j$; X_t is the $N(N-1) \times K$ matrix of explanatory variables whose rows are $x_t' = \left(z_{i,t}^{'}, z_{j,t}^{'}, c_{i,t}^{'}, c_{j,t}^{'}\right)$; ϕ is the conformable vector of β and γ parameters; μ is the $N(N-1)$ vector of fixed effect parameters; and U_t is the $N(N-1)$ vector of the disturbances. The standard heteroscedasticity can be accommodated by letting

$$Var(U_t) = \sigma^2\Omega_t \tag{5}$$

where Ω_t is a $N(N-1) \times N(N-1)$ matrix whose diagonal elements are unity and its off diagonal elements are proportional to the relevant factor that represents the link between the corresponding locations; e.g. an inverse distance matrix is commonly used in the literature whose diagonal elements are unity while the off-diagonal elements are inversely related to D_{ij}. Alternatively, we can model heteroscedasticity using spatially correlated disturbances by assuming

$$U_t = \rho\Pi U_t + V_t, \quad V_t \sim N(0, \sigma^2 I), \tag{6}$$

where Π is the spatial autocorrelation matrix whose elements measure the degree of potential interaction between provinces – or some interdependence between the bilateral migration flows – which could not be modelled directly and would be effective if the scalar parameter $\rho \neq 0$. Combining (4) and (6) we obtain the augmented regression equation which embeds special residual correlation, namely

$$F_t = X_t\phi + \mu + (\mathrm{I} - \rho\Pi)^{-1}V_t, \tag{7}$$

that can be estimated by least squares using the appropriately weighed F_t and X_t. A more thorough approach would be to consider the spatial autoregressive model with spatially autocorrelated errors, which combines the following generalisation of (4) that allows for a spatial autoregressive term,

$$F_t = \lambda\Psi F_t + X_t\phi + \mu + U_t, \tag{8}$$

with (6). The elements of matrix Ψ are the spatial autoregressive coefficients whose overall effect is captured by the scalar parameter, λ. One can then consider the following special cases: $[\rho = 0 \ \& \ \lambda = 0]$; $[\rho \neq 0 \ \& \ \lambda = 0]$; $[\rho = 0 \ \& \ \lambda \neq 0]$; and $[\rho \neq 0 \ \& \ \lambda \neq 0]$. The diagonal elements of both Ψ and Π are, by definition, zero and while there are circumstances in which their off-diagonal elements, which are fixed a priori to reflect the nature of the interdependence, could be considered as identical, the use of an 'inverse distance' measure for one and a 'standardized contiguity' measure for the other is not uncommon in the literature.[14] We shall report estimates based on all these cases.

4.2. *Evidence*

The distribution of migration flows are depicted in Figure 5 which shows that, on the whole, $\ln M_{ij}$ can be treated as a continuous measure that justifies the use of least squares method to estimate the parameters of our proposed log-linear model in (3).

Figure 5. Distribution of inter-province migration flows

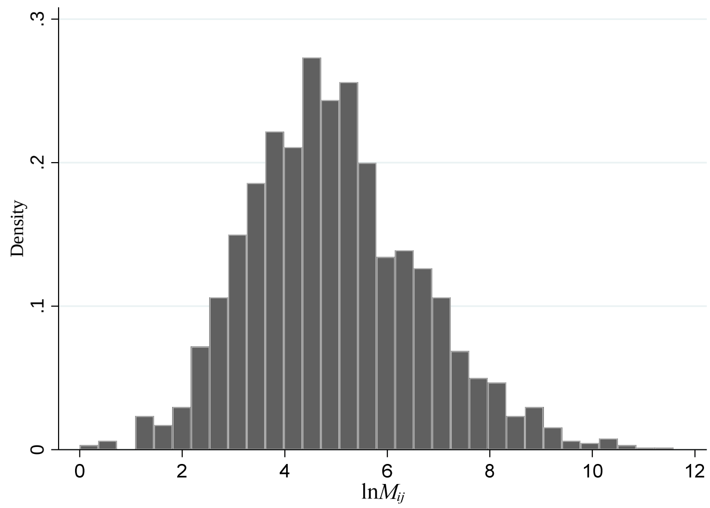


Table 2 presents our OLS estimates of different versions of equation (3). The impacts of climate factors are reported in the lower panel of the table. Column A gives the estimates excluding the latter and can be compared with: (i) columns B to E where we add separately each of temperature or precipitation measures – $\ln T, TD, \ln PR$ and PRD – one at a time; and (ii) columns F and G where we add both measures together – $(\ln T, \ln PR)$ and (TD, PRD) respectively – on the grounds that their linear combination could better captures the climate effect.

[14] See Anselin (2003), LeSage and Pace (2009) and Belotti et al. (2017) for details of formulation and estimation of the above models as well as their more general versions, and Bolduc et al. (1992) for different specifications of spatial weight matrices.

Table 2. OLS estimates of parameters of different versions of equation (3)

Regressors	**A**	**B**	**C**	**D**	**E**	**F**	**G**
$\ln D_{ij}$	-1.714***	-1.719***	-1.715***	-1.727***	-1.731***	-1.730***	-1.733***
$\ln A_i$	0.410***	0.340***	0.412***	0.275***	0.350***	0.221***	0.353***
$\ln P_i$	1.738***	1.529***	1.751***	1.768***	1.828***	1.561***	1.851***
$\ln P_j$	0.529	0.580	0.277	0.204	0.0627	0.256	0.0368
$\ln Y_i$	0.107**	-0.0236	0.115**	0.114**	0.0743	-0.00984	0.0835
$\ln Y_j$	0.903***	0.515**	0.990***	0.901***	1.102***	0.571***	1.138***
G_i	0.0456***	0.0345***	0.0461***	0.0466***	0.0551***	0.0360***	0.0557***
G_j	0.00942*	0.00641	0.0113**	0.0184***	0.0256***	0.0144**	0.0260***
$GINI_i$	0.131	-0.376	0.0433	-0.387	0.262	-0.812	0.162
$GINI_j$	0.857	0.313	1.084	0.885	1.004	0.449	1.053
INF_i	0.0151***	0.0116***	0.0142***	0.0127***	0.0102***	0.00960***	0.00918***
INF_j	0.00559	0.00921**	0.00474	0.00670	0.00575	0.00958**	0.00537
UR_i	0.00596	0.00114	0.00583	0.0100**	0.00201	0.00512	0.00186
UR_j	0.00857	0.00841	0.00645	0.0160	0.0270	0.0133	0.0272
ER_i	-0.00798	-0.00838	-0.00882	0.00439	-0.000403	0.00284	-0.00134
ER_j	0.00687	-0.000329	0.00823	0.00806	0.00968	0.00420	0.00924
RPS_i	0.0349***	0.0281***	0.0354***	0.0416***	0.0390***	0.0342***	0.0399***
RPS_j	-0.0381***	-0.0255***	-0.0417***	-0.0306***	-0.0297***	-0.0210**	-0.0311***
$\ln RHD_i$	-0.213**	-0.128	-0.225**	-0.148*	-0.193**	-0.0746	-0.206**
$\ln RHD_j$	0.798***	0.594***	0.815***	0.742***	0.862***	0.547***	0.889***
$\ln HPD_i$	-0.320***	-0.365***	-0.285**	-0.166	-0.355***	-0.224**	-0.315**
$\ln HPD_j$	-0.998***	-0.935***	-0.956***	-0.963***	-1.140***	-0.876***	-1.152***
RR_i	-0.00394**	-0.00307*	-0.00403**	-0.00634***	-0.00393**	-0.00528***	-0.00405**
RR_j	-0.00239	0.00241	-0.00345	-0.00195	-0.00373	0.00231	-0.00428*
RD_i	-0.00470	-0.00530*	-0.00476	-0.0103***	-0.00406	-0.0103***	-0.00418
RD_j	-0.187	0.447	-0.750	-0.450	-0.656	0.0228	-0.738
$\ln T_i$	--	0.706***	--	--	--	0.664***	--
$\ln T_j$	--	-1.636**	--	--	--	-1.172	--
TD_i	--	--	0.00432	--	--	--	0.00484
TD_j	--	--	0.00924	--	--	--	0.00166
$\ln PR_i$	--	--	--	-0.323***	--	-0.293***	--
$\ln PR_j$	--	--	--	-0.357**	--	-0.301*	--
PRD_i	--	--	--	--	-0.0108***	--	-0.0108***
PRD_j	--	--	--	--	-0.00601***	--	-0.00600***

- The sample size is 1740, consisting of a balanced combination of 30 provinces over the two census periods covering 1996-2011.
- All regressions include an intercept and both province and period (or census) fixed effects. Therefore $\ln A_j$ is dropped to avoid the collinearity.
- '*', '**' and '***' respectively denote significance at 10%, 5% and 1% critical levels based on Huber/White heteroscedasticity-robust standard errors. See notes to Table 3 for diagnostics.

In all cases, the coefficient of distance has the anticipated negative sign, is highly significant and its estimated values are, in fact, not much different from the expected theoretical size of $\delta = -2$. Moreover, based on partial correlation analysis (not reported), $\ln D_{ij}$ appears to be the single most important determining factor as it explains on average about 23% of variations in $\ln M_{ij,t}$, which is considerable. According to our sample, the origin-destination weighted average distance, $\sum_t \sum_i \sum_j M_{ij,t} D_{ij} / \sum_t \sum_i \sum_j M_{ij,t}$, is 575km which is less than the average distance between all pairwise provinces, $\sum_i \sum_{j>i} D_{ij} / [(N^2 - N)/2]$, of 867km. This evidence is consistent with the hypothesis that the relocation cost factor is effective and migrants tend to move to closer provinces with more suitable conditions.

The effects of elements of z_i and z_j vectors – whose weighted average is assumed to capture the 'size' or 'mass' effect of the origin and destination provinces – are on the whole consistent with the underlying theoretical priors. In particular, apart from the Gini coefficient, unemployment rate and education – $GINI,\ UR,\ ER$ – which do not seem to play a significant explanatory role, we find:

(i) Both the area and population of the origin, A_i and P_i, have a positive and statistically significant coefficients in all cases while the destination population, P_j, plays no significant role.[15] Thus, the large physical size of the origin province is a push factor: *ceteris paribus*, the bigger is a province the larger is the number of people leaving it. Given the log-linear specification, the joint impact of these two variables can be rewritten as $\hat{\beta}_{Pi} \ln P_i + \hat{\beta}_{Ai} ln A_i \equiv \hat{\beta}_{Pi} ln(P_i/A_i) + (\hat{\beta}_{Ai} + \hat{\beta}_{Pi}) ln A_i$ which expresses the effect in terms of population density and area and shows that the effect of the area is further enhanced when we account for population density rather than for population size.

(ii) GDP at destination, Y_j, too has a positive and statistically significant effect throughout. This is consistent with the overwhelming evidence that better income opportunities act as pull factor. The coefficient of Y_i, on the other hand, becomes statistically insignificant when we add both climate factors together.

(iii) Growth rates at both origin and destination, G_i and G_j, have positive and statistically significant coefficients throughout. Thus, as expected, economic growth seems to stimulate mobility in general.

(iv) Among the rest of the variables: inflation, especially at the origin, stimulates migration; rurality of origin (destination) stimulates (discourages) migration; better health service provision on the whole and a more fertile land at the origin dampen migration.

The above results are consistent with the theoretical priors and tally with those reported in other studies of cross-location migration flows – see, Ruyssen, et al. (2014) and Backhaus et

[15] The destination area, A_j, was dropped to avoid collinearity as all regressions included province and period fixed effects as well as a constant intercept.

al. (2015), amongst others. Turning to the effect of climate variables we find that adding these, once all other determining factors are accounted for, does not alter by much the estimated values of the other coefficients and both temperature and precipitation levels play a significant role. In particular, a higher (lower) average annual temperature at the origin (destination) acts as push (pull) factor whilst a rise in precipitation in general dampens migration flows. This evidence is consistent with those reported in other studies of cross-location migration flows – see, e.g., Andersen et al. (2010) and Joseph and Wodon (2013) – and confirms that, in addition to taking account of distance, economic opportunities and well-being factors, people do care about climatic conditions when deciding to migrate to another location within the country. In addition, we find that including both temperature and precipitation measures together as explanatory variables improves the regression fit. Table 3 reports the relevant diagnostic statistics for regressions presented in columns of Table 2. Based on these, the specification in column F which includes both temperature and precipitation levels statistically dominates the rest.

Table 3. Diagnostic statistics for regressions reported in Table 2

Statistic	**A**	**B**	**C**	**D**	**E**	**F**	**G**
R^2	0.836	0.841	0.836	0.840	0.843	0.845	0.843
$\bar{R}^2$	0.830	0.836	0.830	0.834	0.838	0.839	0.838
RMSE	0.651	0.640	0.651	0.643	0.637	0.634	0.637
RSS	712.4	688.3	711.8	695.6	681.5	674.8	681.0
L	-1692.0	-1662.1	-1691.3	-1671.3	-1653.5	-1644.9	-1652.8
AIC	3498.0	3442.1	3500.5	3460.7	3424.9	3411.8	3427.6
BIC	3809.3	3764.3	3822.7	3782.9	3747.2	3744.9	3760.7
RESET	11.14 (0.000)	12.10 (0.000)	11.23 (0.000)	10.33 (0.000)	11.62 (0.000)	11.24 (0.000)	11.66 (0.000)

RMSE, *RSS*, *L*, *AIC* and *BIC* respectively denote root mean square error, sum of squared residuals, log-likelihood value, Akaike and Schwarz information criteria. *RESET* is Ramsey's misspecification test with p-values in parentheses.

While the coefficient estimates reported in Table 2 above provide a good indication of the role of climate factors, they are obtained using the ordinary least squares estimator and therefore do not take account of any inter-province links. However, in all cases (columns A to G in the above tables) the value of *RESET* test statistic lies in the critical region. Since our attempts to include additional, potentially relevant, explanatory variables did not resolve this problem, we are inclined to interpret the possible misspecification implied by the *RESET* test as being caused by the omission of inter-province links. We therefore re-estimated the specification in column F of Table 2, which is the preferred model, by allowing for spatial interactions that combine equations (8) and (6) outlined above. The results, based on estimating different versions of this generalised model, are given in Table 4.

Table 4. Comparing the OLS and spatial autoregressive estimates of the climate effects

Estimation Method	Climate Factor Coefficients				Spatial Coefficients		Goodness of Fit Statistics				
	$\ln T_i$	$\ln T_j$	$\ln PR_i$	$\ln PR_j$	$\hat{\rho}$	$\hat{\lambda}$	residual $\hat{\sigma}^2$	overall R^2	L	AIC	BIC
OLS	0.664	-1.172	-0.293	-0.301	--	--	0.402	0.845	-1644.9	3411.8	3744.9
$\Pi = \Psi = 0$	(5.12)	(1.52)	(4.69)	(1.82)							
SEM	0.629	-1.261	-0.331	-0.306	1.437	--	0.381	0.830	-1632.3	3324.6	3488.5
$\Pi = H, \Psi = 0$	(6.62)	(0.68)	(6.34)	(1.30)	(26.85)						
SEM	0.541	-1.081	-0.325	-0.308	0.330	--	0.387	0.834	-1643.8	3347.6	3511.4
$\Pi = B, \Psi = 0$	(3.07)	(0.61)	(5.18)	(1.32)	(0.97)						
SAR	0.660	-1.161	-0.295	-0.301	--	0.0266	0.388	0.838	-1644.8	3347.6	3506.0
$\Pi = 0, \Psi = B$	(7.00)	(0.64)	(5.55)	(1.27)		(0.28)					
SAC	0.533	-1.061	-0.332	-0.309	0.347	0.0437	0.387	0.833	-1643.6	3351.2	3526.0
$\Pi = \Psi = B$	(3.35)	(0.59)	(5.19)	(1.33)	(1.09)	(0.44)					
SAC	0.622	-1.201	-0.335	-0.313	1.453	0.0483	0.381	0.830	-1632.1	3330.3	3510.5
$\Pi = H, \Psi = B$	(7.15)	(0.64)	(6.38)	(1.33)	(29.55)	(0.49)					

- **SAC** refers to the full spatial autocorrelation model, $F_t = \lambda\Psi F_t + X_t\phi + \mu + U_t$; $U_t = \rho\Pi U_t + V_t$; $V_t \sim N(0, \sigma^2 I)$ and **OLS**, **SEM** and **SAR** are the special cases, respectively with: no spatial correlation, only correlated disturbances, and only autoregressive term. Coefficient estimates are obtained using the "*xsmle*" Stata syntax outlined in Belotti et al. (2016).
- The figures in parentheses are t-ratios clustered on destination provinces. The number of observations in all cases is 1740.
- The H matrix is constructed with elements $h_{ij} = A_i A_j / D_{ij}^2, i \neq j$, $w_{ij} = 0, i = j$ – where A_i, A_j and D_{ij} are the areas of provinces i and j and the distance between them – which are suitably normalised and truncated.
- The B matrix is constructed using a dummy, ω_{ij}, that takes the value of unity if the two provinces i and j are 'contiguous' and zero otherwise, and the elements of B are then set to $b_{ij} = \omega_{ij} / \sum_j \omega_{ij}$.

A comparison of the estimates reported in Table 4 suggests that there is clearly a significant inter-province interaction which is best picked up by allowing for spatially correlated disturbances using a modified version of the inverse distance matrix for weights; see the row corresponding to "$\Pi = \mathrm{H}, \Psi = 0$" where the estimate of ρ, the parameter that captures the correlation effect, is highly significant. As the other rows show, using the contiguity matrix instead and/or allowing for spatial autocorrelation does not seem to add much, and on the whole the coefficient estimates of temperature and precipitation maintain their size and sign and their statistical significance consistently conveys their influence on migration decision.

5. Summary and conclusions

In this paper we have empirically examined the existence and robustness of the relationship between climatic factors and internal migration in Iran. This was motivated by the need for providing evidence in support of the received wisdom that climate change induces migration. We have focused our analyses on internal migration in a single county since it excludes other major types of migration – that are, e.g., induced by political and religious factors, etc. – and have chosen Iran because it has become increasingly vulnerable to climate change and has had a recent history of significant internal migration. Iran's census data, which are a reliable source of information on population mobility within the country, provided us with an opportunity to empirically test the hypothesis that climate change induces migration above and beyond that caused by the socio-economic factors.

Our results, which are based on the period 1996-2011 covering the last two censuses, suggest that, apart from economic growth and cost of relocation – proxied by the average rate of growth of real GDP and distance – which respectively induce and discourage mobility, typical pull/push factors – size, income opportunities, health provision, rurality, etc. – play the expected role in driving internal migration in Iran. We also find that climatic factors play a significant role in explaining internal migration in Iran once all other relevant effects are accounted for. Using average annual temperature and precipitation levels as proxies for climate factors, our results show that a rise in temperature and a drop in precipitation act as significant push factors and these results are robust to inter-province links captured by spatial correlation.

As an indication of the magnitude of the climatic impact on internal migration in Iran, according to our estimates:

- A one s.d. rise in annual temperature, which is equivalent to becoming 4^{o}C hotter, would lead to 15.4% more emigration. Alternatively, a one s.d. rise in temperature with respect to the climate average, which is equivalent to becoming 0.7^{o}C warmer, would increase emigration by 8.3%.
- A reduction of 260mm in annual rainfall, which is equivalent to one s.d. fall in annual precipitation, would raise emigration by 20.5%. Alternatively, a one s.d. fall in precipitation with respect to the climate average, which is equivalent to 55mm less rainfall, would stimulate 15.4% increase in emigration.

Our results are sufficiently robust to invoke policy concerns. Since migrants seem to target locations with better income and welfare opportunities, at the going rate they could soon crowd out such locations while conditions in the rural areas which they leave behind rapidly deteriorate. This is a potentially alarming situation since a steady unregulated migration could irreparably damage the regional and environmental balance of the country. The policy implications are unambiguous: there needs to be a strong collaboration between authorities responsible for industrial development, regional planning, urbanisation, demographic, environment and climate change policies since the harmful consequences resulting from a vicious circle of deterioration of rural regions and over-crowding of the urban regions could be practically irreversible.

An immediate policy response could target capacity building and adaptation measures which aim to improve localised resilience so as to reduce the impact of specific climatic effects. Clearly, there are different ways of stimulating localised resilience amongst which the following policies have received some attention:

- introducing micro-insurance for compensating the impact of climate-based anomalies, e.g. a rainfall insurance where pay-out is triggered when rainfall deviation reaches a certain threshold level, as proposed by Gine et al. (2008) and Hertel and Rosch (2010);
- implementing targeted forest cultivation and drought resistant crop policies – see Farzin (2014) and Lilleør and Van den Broeck (2011) respectively; and
- promoting individual-level innovation via development of sustainable and appropriately targeted micro-finance schemes which prioritise artisan traditional agricultural activities that utilise suitable irrigation methods.

Article 4.4 of the United Nations Framework Convention on Climate Change states that "*developed country Parties ... shall ... assist the developing country Parties that are particularly vulnerable to the adverse effects of climate change in meeting the costs of adaptation to those adverse effects*".[16] There is a strong incentive for countries such as Iran to exploit this opportunity by providing robust evidence of the impact of climate factors, putting forward innovative plans and seeking funding and expert advice to tackle the problem at its early stages.

Given the encouraging and informative nature of the evidence provided here, further research should give priority to identifying, and enhancing our understanding of the role of, the push and pull factors which motivate migration. To this end, combining data from different countries would help in assessing more precisely the role of climatic factors which are bound to play an increasingly dominant role.

[16] See Barr et al. (2010) for an overview and Klein (2009) for a discussion of '*vulnerability*' in this context.

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