ORIGINAL ARTICLE

Air pollution and internal migration: evidence from an Iranian household survey

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Abstract

Air pollution has become an important national issue in Iran in recent years. Several studies in Iran have shown that air pollution harmfully impacts the physical and mental health of citizens, reducing labor productivity and student academic performance. One aspect of air pollution that is yet to be examined is if it explains migration behavior across the provinces of Iran. Between 2011 and 2016, approximately 4.3 million Iranians (about 5% of the population) left their habitual residences and moved to new locations (mostly within the borders of Iran). The purpose of this study is to examine the effect of air pollution (measured using satellite data of aerosol optical depth) on net outmigration. We used data from the 2011 and 2016 *National Population and Housing Censuses* for 31 provinces in Iran and applied panel fixed effects and instrumental variable procedures to analyze the data. Our results show that air pollution has a positive and significant effect on net outmigration. We also found that higher levels of economic activities discourage outmigration.

Keywords Air pollution · Migration · Economic activities · Iran

JEL Classification Q53 · R23

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1 Introduction

Air pollution in Iran has attracted international attention. Reuters (May 12, 2016) reported, "Iranian, Indian cities ranked worst for air pollution." According to Voice of America, at the end of 2019, air pollution had reached critical levels in several major urban areas in Iran, forcing the government to shut down schools and universities for weeks (VOA 2019). This media coverage reflects the significant challenges of air pollution and its harmful impact on Iranian citizens.

According to the 2018 Environmental Performance Index (EPI 2018), Iran was ranked 167 out of 180 countries in terms of air pollution (measured by sulfur oxides (SOX) and nitrogen oxides (NOX)). Es'haq Jahangiri (the first Vice President of Iran) noted that the environment was one of the top four problems of the country (Radiofarda 2017). The key sources of air pollution in Iran are transportation, the extensive use of fossil fuels, outdated urban fleets of gasoline and diesel vehicles, industrial sources within and close to city boundaries, and natural dust (Hosseini and Shahbazi 2016).

Diseases associated with air pollution kill about 35,000 people every year in Iran, according to an official at the Environmental Protection Organization (Darvish 2017). In addition, several studies in Iran have shown that air pollution negatively affects physical health (e.g., causing asthma, respiratory illness, cardiovascular disease, and cancer), mental health (e.g., causing anxiety and depression), labor productivity, and student academic performance (Ghorani-Azam et al. 2016; Hosseini and Shahbazi 2016; Neisi et al. 2016; Birjandi and Yousefi 2017; Esmaeilpour Moghadam and Dehbashi 2018; Amanzadeh et al. 2020). One aspect of air pollution that is yet to be examined is whether air pollution explains migration behavior across the provinces of Iran.

While air pollution has become one of the most important national issues in recent years, pollution levels within Iran vary widely, with some provinces such as Sistan and Baluchestan (located in the southeast of the country) and Khuzestan (located in the southwest) being significantly affected. In contrast, northern provinces, such as Mazandaran and Gilan, have experienced less severe pollution. Therefore, the considerable cross-sectional variation in air pollution offers an interesting context to test the relationship between air pollution and migration across Iran's provinces.

Between 2011 and 2016, approximately 4.3 million Iranians left their habitual residences and moved to new locations (mostly within the borders of Iran).[1] This raises the question of whether air pollution has driven residents from their habitual residences.

The purpose of this study is to examine the impact of air pollution on domestic migration using data from the 2011 and 2016 *National Population and Housing Censuses* for the 31 provinces of Iran. While some studies have tested the relationship between air pollution and actual migration (as well as the intention to migrate) in China and the USA (e.g., Cebula and Vedder 1973; Hsieh and Liu 1983; Kahn 2000; Chen et al. 2017; Lu et al. 2018; Qin and Zhu 2018; Levine et al. 2019), to the best of our knowledge, little is known about the pollution–internal migration nexus in one of

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[1] The information is available at https://www.amar.org.ir/Portals/0/Files/fulltext/1395/n_ntsonvm_95-v2.pdf (in Persian).

the most polluted regions of the world, the Middle East (Gholipour and Farzanegan 2018).

In this study, we utilize satellite-based air pollution data from major cities in each province, migration data (obtained from the 2011 and 2016 *National Population and Housing Censuses*), as well as province-level macroeconomic and climatic factors to analyze the relationship between air pollution and migration across the provinces of Iran. By applying panel fixed effects and two-stage least squares (2SLS) estimators, we find that air pollution has been one of the key drivers of internal migration across Iran's provinces over the past decade.

The article proceeds as follows: The second section reviews previous studies and develops the hypothesis. The third section describes the data and variables and explains the estimation method. The fourth section presents the findings, and the fifth section concludes the article.

2 Previous studies and hypothesis

Existing studies have shown that air pollution triggers avoidance behavior (e.g., avoiding outdoor activities), defensive expenditure (e.g., spending on air purifiers and facemasks), and migration as coping strategies (Lu 2020). In terms of migration, several studies have found that residents in polluted locations tend to exhibit greater interest in emigration. For example, Qin and Zhu (2018) found that Chinese residents search for the word "emigration" more often on online search engines when the level of air pollution rises significantly. Their study used data from 153 major Chinese cities in 2014. Likewise, Lu et al. (2018), using survey data collected in 2015, found a positive and strong relationship between smog risk perception (including perceptions of physical and mental health risk) and migration intention among skilled workers in the Jing–Jin–Ji region of China. Chen et al. (2017) also showed that air pollution significantly affected changes in inflows and outflows of migration in Chinese counties during the 1996–2010 period.

Hsieh and Liu (1983) provided evidence in the USA that better quality of social life and environmental quality is the dominant factor in explaining interregional migration in the long and short term, respectively. Kahn (2000) showed that reduction in smog problems in Los Angeles (due to the Clean Air Act regulation) and, consequently, a higher quality of life, fostered migration flows toward the city. Gawande et al. (2000) found that proximity to hazardous waste sites in the USA was a contributing factor in the migration decisions of individuals whose incomes were over a certain level. Using information on the career paths of executives in S&P 1500 firms, Levine et al. (2019) found that air pollution has a positive impact on the migration of highly valued US employees from firms that are geographically close to polluting plants. They also found that executive departures have adverse effects on corporate stock prices. However, Cebula and Vedder (1973) did not find a significant relationship between air pollution and migration within US metropolitan statistical areas over the 1960–1968 period. Similarly, Hunter (1998) showed that US counties that pose high levels of environmental hazards (such as air and water pollution, hazardous waste, and superfund sites) do not lose residents at greater rates than those without such hazards.

She also found that counties characterized by high levels of environmental risk have lower in-migration rates than counties with fewer hazards. At the international level, Xu and Sylwester (2016) showed that immigration to OECD countries from other countries was affected by air pollution in the source countries.

The main argument of the above-mentioned studies is that a location's environmental quality (as an important component of quality of life) plays a role in shaping individual and household internal and international migration decisions (Kahn 2000; Hunter 2005). This argument is closely related to the theoretical work of Wolpert (1996), who was among the first to explain the relationship between non-economic variables (environmental quality) and migration behavior. More specifically, Wolpert (1996) argued that migration is a response to stress experienced from the current residential location, with residential "stressors" such as environmental dis-amenities such as pollution, congestion, and crime. Wolpert's model suggests that these "stressors" bring about "strain," which may lead to consideration of residential alternatives (Hunter 2005).

To the best of our knowledge, empirical examination of the effect of air pollution on internal migration in Iran is lacking. There are different factors that contribute to domestic outmigration in Iran, such as economic deprivation, unemployment, and climate change, which has shown its effects through frequent droughts, flooding, and sandstorms.[2] Understanding internal migration patterns and the role of environmental quality in Iran's development is important for policymakers. Recent nationwide protests in response to increased gasoline prices in Iran showed significant participation of people from the vicinity of larger cities. In these areas, around 11 million poor Iranians live without access to many urban amenities (Sinaiee 2019). Various factors may lead to an expansion of the population around major urban areas in Iran. We contribute to the literature by examining the extent at which economic and environmental issues are fueling internal outmigration, expanding the slum population in Iran.

Based on our review of the literature and the stylized facts of Iran, the main hypothesis is as follows:

Hypothesis: Provinces with higher degrees of air pollution experience a higher level of net outmigration, *ceteris paribus*.

3 Data and estimation method

3.1 Dependent variable

The dependent variable of the study was the net outmigration ratio (Gawande et al. 2000), defined as the population leaving two major cities of a province minus new arrivals, divided by their combined total population. We collected data on the inflows and outflows of migration from two major cities in each province of Iran, available from the 2011 and 2016 *National Population and Housing Censuses* (conducted by the

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[2] Farzanegan et al. (2020) examine the economic impacts of drought on property values within Iranian provinces.
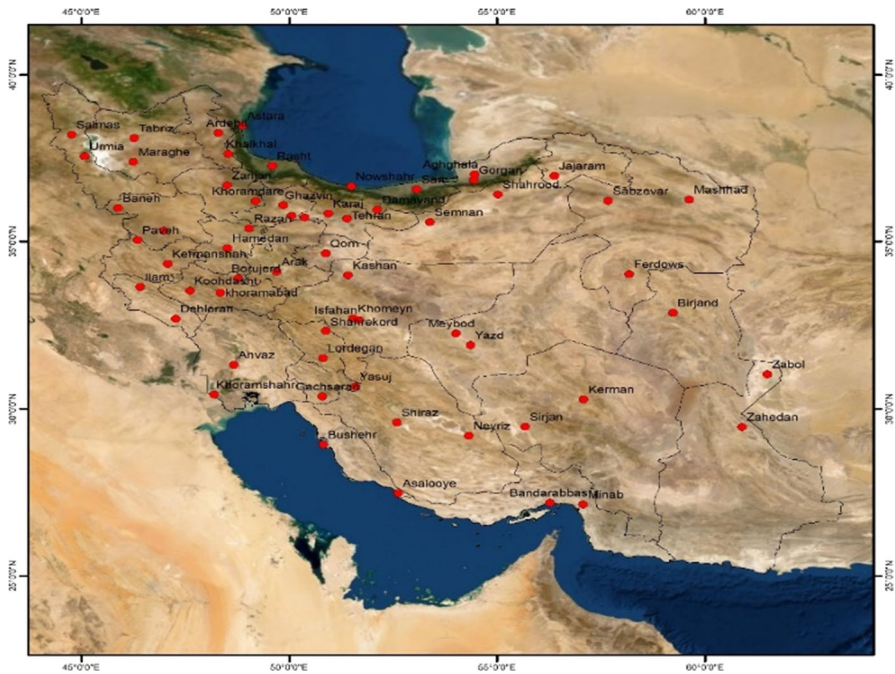
Fig. 1 Location of sample cities on Iran's map

Statistical Center of Iran[3]). The choice of the 2011 and 2016 censuses for the analysis was based on the availability of inflow and outflow migration data. In addition to the availability of data, we focused on the two major cities because most economic and migration activity in each province occurs in these cities. Aerosol optical depth ("AOD") also measures the air pollution in the included major cities of each province. We used the total number of migrations in the province's two major cities as a measure of migration for each province. Figure 1 shows the location of each sample city on Iran's map.

The net outmigration ratio varied from a minimum of − 0.08 (Semnan in 2016) to a maximum of 0.06 (Lorestan in 2011 and Chaharmahal Bakhtiari in 2011), with an average of − 0.003. In total, 50% of the provinces have a net outmigration ratio of less than zero, while the net outmigration ratio of others exceeds this level. Table 6 in Appendix provides detailed descriptive statistics for the various quartiles of the net outmigration ratio.

3.2 Variable of interest

The main explanatory variable of interest, AOD, measures air pollution. Aerosols are very small solid and liquid particles that are suspended in the atmosphere. Examples of aerosols include dust, sea salts, volcanic ash, smoke from wildfires, and pollution

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[3] See https://www.amar.org.ir/english/Population-and-Housing-Censuses.

from factories. The inhalation of aerosols is often associated with increased morbidity and mortality. Long-term excessive exposure to aerosols leads to higher risks of lung cancer, chronic obstructive pulmonary diseases, ischemic heart disease, and strokes (Traboulsi et al. 2017).

We used remote sensing data to measure AOD across the provinces of Iran. In particular, we employed the moderate resolution imaging spectroradiometer (MODIS), which is a key instrument aboard the Terra (originally known as EOS AM-1) and Aqua (originally known as EOS PM-1) satellites. The Terra MODIS and Aqua MODIS constantly monitor the entire Earth's surface. They collect information on global dynamics and processes occurring on land, in the oceans, and in the lower atmosphere.[4] They have been measuring global aerosol optical depth and optical properties since 2000 (van Donkelaar et al. 2010).

MODIS aerosol products are freely available and are being used in several studies for different purposes. MODIS AOD has shown a good relationship with ground measurements (Mardi et al. 2018; Shi et al. 2019). The data to measure AOD in our study of Iranian provinces were sourced from NASA Earthdata.[5] The average AOD values in the study area are illustrated in Fig. 2. It shows that the southern part of Iran has suffered more from air pollution compared to the northern part. Dust storms are the main source of AOD in Iran, except in metropolitan cities (e.g., Tehran and Isfahan), where urban pollutants typically dominate. The deserts in Iraq, Saudi Arabia, and Syria, as well as local soil erosions are the main dust sources in Iran. Therefore, the southern and western provinces of Iran have higher AOD than the northern provinces. Based on Fig. 2, Zahedan, Zabol, Ahvaz, Khorramshahr, and Urmia were the most polluted cities in Iran during the period of our study.[6]

The AOD measure changed from a minimum of 0.16 (Ardebil in 2016) to a maximum of 0.41 (the oil-based province of Khuzestan in 2011), with an average of 0.26. Of the provinces in our sample, 50% have AOD values below 0.25, while the AOD values of other provinces exceed this level. Table 6 in Appendix provides a detailed set of descriptive statistics for the various quartiles of AOD. For 2011, we used the average AOD of the 2007–2011 period. For 2016, we used the average AOD of the 2012–2016 period.[7]

Figure 3 shows the scatter plot of the net outmigration ratio and AOD. The positive slope of the trend line illustrates our main result. To show the positive link, we also provide a numerical example. When the annual mean AOD of Khorramshahr (in the Khuzestan province) and Zabol (in Sistan and Baluchestan province) increased from 0.36 and 0.29 in 2011 to 0.43 and 0.35 in 2016, respectively, their outmigration also increased from 7905 to 9872 and from 16,534 to 21,772, respectively. In contrast, in Nowshahr (in the Mazandaran province), when the annual mean AOD was stable at

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[4] See https://modis.gsfc.nasa.gov/about/.

[5] See https://earthdata.nasa.gov/.

[6] We embedded the interactive map and its JavaScript code in Google Earth Engine, and it is publicly available at: https://code.earthengine.google.com/31d7026e72b575db9e6d2e33e7769a9a.

[7] Note that this approach assumes that the pollution situation over the past years, including the year of the survey, explains the level of net outmigration during the year of the survey, reducing the effect of reverse feedback.
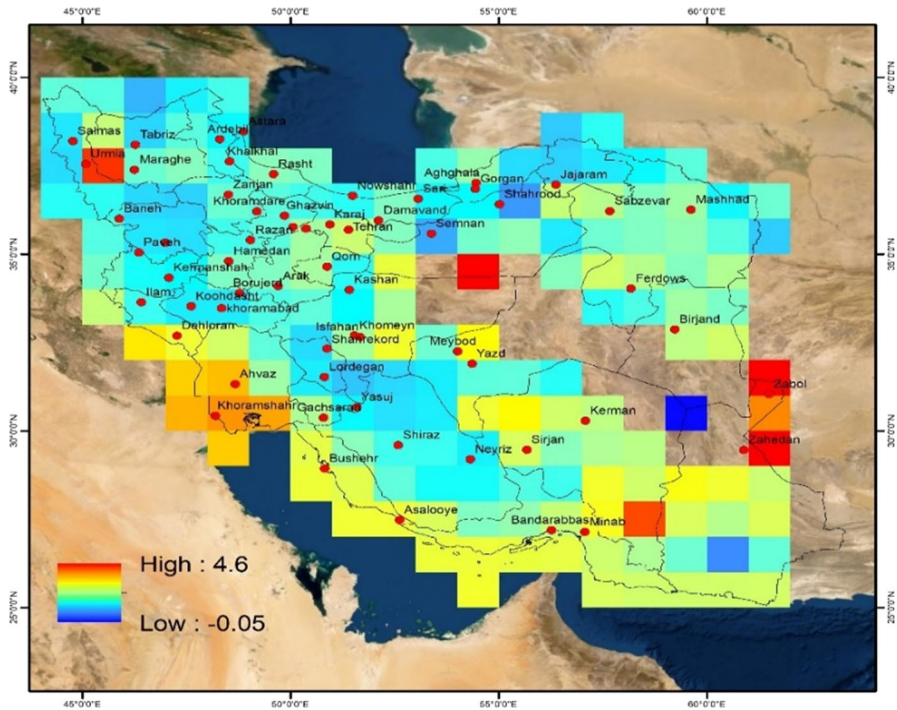
Fig. 2 Averaged AOD of cities included in our study over the 2007–2016 period. *Source:* Our own calculations based on NASA Earthdata. *Note*: The maximum AOD is in the Eastern grid of Zahedan (capital of Sistan and Baluchestan province in the South East), (AOD = 4.6), and we do not have any cities in that grid. In addition, the minimum AOD is in the Loot Desert, in an area between Kerman and Zahedan (AOD = − 0.05), and we do not have any cities there either. For this reason, the minimum and maximum of this map do not match the summary statistics of our sample data for the minimum/maximum AOD. In other words, our studied cities were not among the min/max cities

approximately 0.20 between 2011 and 2016, outmigration changed only slightly from 6445 to 6619, which is consistent with changes in AOD.

3.3 Control variables

In addition to our variable of interest (AOD), we also controlled for other key determinants of internal net outmigration. The choice of control variables was based on our literature review of the determinants of internal migration and the availability of data for the provinces of Iran. Our control variables are the level of economic activity in the source province, unemployment rate, amenities, environmental quality indicators, and income inequality. Table 1 provides a detailed description of the variables and data sources. Descriptive statistics are presented in Table 2. In the following section, we briefly explain the relationship between each control variable and migration.
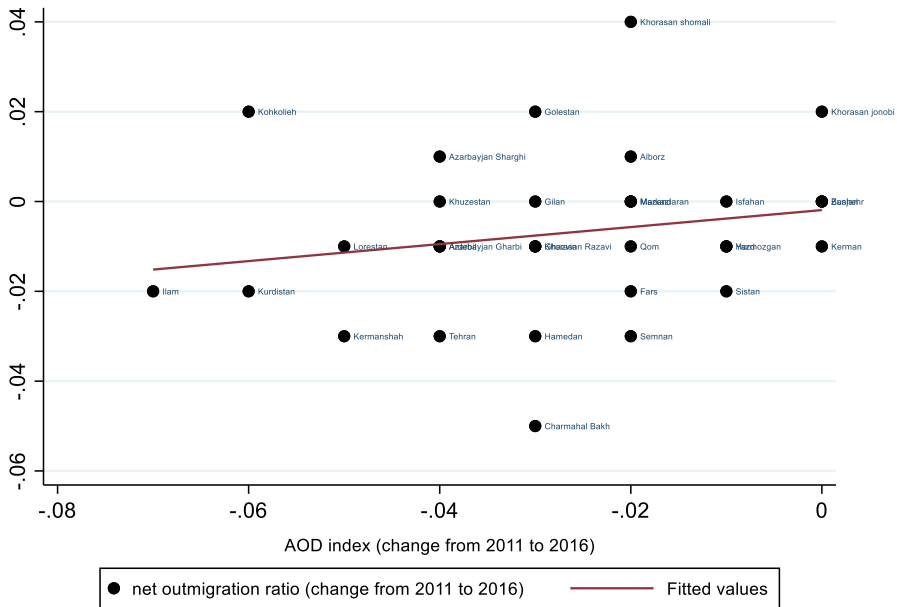
Fig. 3 The association between net outmigration (EMIG_OUTRATIO) and AOD

3.3.1 Economic activity

Existing studies have shown that a lower level of economic development in the source locations is an important incentive factor for emigration (Hunt 2006; Ruyssen et al. 2014). This is because more economic activity creates more opportunities for various sources of income (e.g., higher wages, rents), discouraging local people from leaving their place of birth. We used real gross domestic product (GDP) per capita as a proxy for economic activity and expect that the net outmigration ratio would be lower in provinces of Iran where the level of economic activity was higher.

3.3.2 Unemployment

We used the province-level unemployment rate (among populations above 10 years old). Existing research shows that the relationship between unemployment (or employment opportunities) in the source country and migration is inconsistent, and that it depends on the period of study and sample countries (or regions). For example, Ruyssen et al. (2014) used data from 19 OECD countries between 1998 and 2007 to show that migration is positively and significantly affected by employment rates in the host country. On the other hand, Hunt (2006) found the link between unemployment and migration flow between East and West Germany to be insignificant (using data from the 16 German states for 1991–2000). Hunt (2006) argued that although high unemployment (and lack of job opportunities) increases an individual's intention

Table 1 Description of variables

Notation	Variables	Definition	Data source	Transformation
EMIGOUT_RATIO	Net outmigration ratio	Outgoing migration minus incoming migration in two major cities of province divided by their combined population	Statistical Center of Iran and Authors' calculation 2011 and 2016 Iranian Population and Housing Censuses	
AOD	Air pollution	The average aerosol optical depth (AOD) of two major cities in each province. For 2011, we used the average AOD between 2007 and 2011. For 2016, we used the average AOD between 2012 and 2016	NASA Earthdata	
GDPC	Economic activities	Real gross domestic product per capita. For 2011, we used the average real GDP per capita of the 2007–2011 period. For 2016, we used the average real GDP per capita of the 2012–2016 period	Statistical Center of Iran	Logarithm
UNEM	Unemployment	Unemployment rate (among population above 10 years old) For 2011, we used the average unemployment rate of the 2007–2011 period. For 2016, we used the average unemployment rate of the 2012–2016 period	Statistical Center of Iran	

Table 1 (continued)

Notation	Variables	Definition	Data source	Transformation
HOSPITAL_POP	Medical facilities	Number of active hospital beds divided by population (in million)	Statistical Center of Iran and Authors' calculation	
RAIN	Average monthly rainfall (milliliter)	For 2011, we used the average monthly rainfall of the 2007–2011 period. For 2016, we used the average monthly rainfall of the 2012–2016 period	The Iran Meteorological Organization	Logarithm
GINI	Gini coefficient	Gini coefficient in urban areas for 2011 and 2015. Higher scores mean higher levels of income inequality	Statistical Center of Iran	
SPEI	Standardized Precipitation-Evapotranspiration Index (SPEI)	This index is based on the difference between precipitation and potential evapotranspiration. It is an improved drought index to study the consequences of global warming on drought severity. Larger values indicating higher degrees of moisture	Farzanegan et al. (2020)	
Temperature	Average annual temperature (Celsius)		The Iran Meteorological Organization	

Table 2 Descriptive statistics

	EMIGOUT_RATIO	AOD	log(GDPC)	UNEM	HOSPITAL_POP	log(RAIN)	GINI	SPEI	Temperature
Mean	− 0.003	0.26	11.01	11.63	28.17	5.487	0.320	− 0.506	16.8
Std. dev	0.028	0.054	0.44	2.58	28.91	0.688	0.034	0.334	4.11
Minimum	− 0.08	0.16	10.16	7.94	6	6.75	0.25	− 1.4	9.77
Maximum	0.06	0.41	12.31	19.3	162	7.18	0.40	0.39	27.17
Observations	62	62	62	62	62	62	62	62	62

to leave, it might cause the individual to be liquidity-constrained and unable to pay migration costs.

3.3.3 Amenities and environmental quality indicators

Several studies provide evidence that availability and provision of quality amenities and climate (e.g., public services, infrastructure, temperature, precipitation, and weather anomalies) discourage migration from source places (e.g., Mueser and Graves 1995; Gawande et al. 2000; Ruyssen et al. 2014; Backhaus et al. 2015; Shiva and Molana 2018). For example, Mueser and Graves (1995) modeled the internal net migration within the USA between 1950 and 1980 and showed that amenities are significant determinants of location decisions. In our study, we used the availability of medical facilities and precipitation as proxies for the quality of amenities and environment in each province of Iran.

3.3.4 Inequality

Existing literature has shown that inequality in the country of origin has a positive and significant relationship with the incentive to migrate and actual migration (e.g., Liebig and Sousa-Poza 2004; Gallardo-Sejas et al. 2006; Stark 2006; Ambinakudige and Parisi 2017; Serlenga and Shin 2020). In a theoretical study, Stark and Wang (2000, p. 131) argued that "a comparison of the income of i (an individual, a household, a family) with the incomes of others who are richer in i's reference group results in i's feeling of relative deprivation. The associated negative utility impinges on migration behavior." In our estimation, we used the Gini coefficient as a measure of income inequality in each province.

3.4 Estimation method

We apply a panel fixed effects model for the estimations.[8] Equation (1) presents the empirical model. The fixed effects model accounts for all time-invariant differences across provinces, such as cultural, traditional, or geographical factors that may affect both air pollution and net outmigration. Provinces of Iran differ not only because of their stage of economic development, but also because of the high degree of ethno-linguistic fractionalization in Iran. Different cultural backgrounds may shape various aspects of the social and economic life of households. For example, the issues of energy consumption, attention to natural resources, and environmental protection also have cultural drivers (e.g., Soyez 2012; Horlings 2015). Cultural norms and differences in risk attitudes may also explain and form migration behavior within and across provinces. In addition, geography may shape the pattern of energy consumption, transportation, and urban life, which may also influence AOD. At the same

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[8] We employed a Hausman (1978) test to compare the fixed and random effects estimates of coefficients. The χ^2 statistic of the test was significant at the 5% level, indicating that fixed effects are appropriate for our models.

time, geography may influence the allocation of the budget by the state and investment rate. Attractive places may accommodate a larger number of investors in various economic sectors (e.g., real estate and tourism) than less geographically attractive locations. The latter may then influence an individual's decision to migrate. For these reasons, we include province fixed effects in our estimations. In fixed effects regressions, we estimate the effect of within-province changes in our explanatory variables on within-province changes in our outcome variable, removing the possible effects of any province-specific time-invariant characteristics. This approach reduces the risk of spurious correlation between net outmigration and AOD. It is noteworthy that several studies on determinants of international and regional immigration have also applied fixed effects estimators (e.g., Clark et al. 2007; Mayda 2010; Arif 2020).

$$\text{EMIGOUT\_RATIO}_{it} = \beta_1 \text{AOD}_{it} + \beta_2 X_{it} + v_i + u_{it} \qquad (1)$$

where EMIGOUT_RATIO is outgoing migration minus incoming migration in two major cities of province divided by their combined population; AOD is the aerosol optical depth (as a proxy for air pollution); X is a vector that includes the control variables; v_i captures the province-specific effects; $i = 1,...;$ n denotes the province; $t = 1, ...;$ t denotes the time period; βs are coefficients; and u_{it} is an error term.[9] Following de Chaisemartin and D'Haultfoeuille (2020), Imai and Kim (2021), and Kropko and Kubinec (2020), we decided not to include time fixed effects because using both province and time fixed effects can obscure interpretation.[10] We use robust standard errors in reporting t-statistics. These standard errors are adjusted for 31 clusters at the province level. They are robust against heteroskedasticity and/or serial correlation in the idiosyncratic error. We also test for panel cross-sectional dependence. It is commonly assumed that disturbances in panel data models are cross-sectionally independent, especially in samples with large number of cross-sectional dimension. However, the existence of cross-sectional dependence maybe present in panel regression. Residual dependence may result in estimator efficiency loss and invalid test statistics. We conducted residual cross-sectional dependence test based on Baltagi, Feng, and Kao Bias-corrected Scaled LM (Baltagi et al., 2012) and Pesaran CD (Pesaran, 2021), which is appropriate for the short time and large cross-sectional dimensions as in our study, after estimating the general model (Model 7 in Table 3). The results show that we cannot reject the null hypothesis of "*no cross-sectional dependence (correlation) in residuals*" with *p*-values of 0.80 and 0.47, respectively.

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[9] We examined the interaction terms between AOD and log of GDP per capita and between AOD and unemployment rate in the estimations. However, these interaction terms were not statistically significant. In addition, we included the squared term of AOD in the estimation model to test if the effects on migration are more serious when pollution increases in provinces that are already severely affected by this problem. The results indicated that the squared term of AOD was insignificant. These findings are available upon request.

[10] Nevertheless, we also estimated the model by including time fixed effects, in addition to province fixed effects. The sign of AOD on outmigration was positive, but its estimated effect was not any more statistically significant at the conventional levels. The coefficient of time fixed effects itself was not also statistically significant when we included it in the model.

Table 3 Panel analysis with province fixed effects: main results

| | Dependent variable: EMIGOUT_RATIO | | | | | | | 2SLS |
| | OLS fixed effects | | | | | | | |
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
AOD index	0.237**	0.311***	0.247**	0.213	0.268***	0.245**	0.346**	0.636***
	(2.37)	(2.81)	(2.63)	(1.62)	(2.76)	(2.48)	(2.31)	(3.07)
Log of GDP per capita		−0.046***					−0.046***	−0.064***
		(−2.89)					(−2.90)	(−4.37)
Unemployment			−0.002				−0.002	−0.001
			(−1.16)				(−1.35)	(−1.03)
Gini index				0.043			−0.016	−0.146
				(0.54)			(−0.19)	(−1.43)
Hospital facility					0.001		0.0002	0.0006
					(1.61)		(0.44)	(1.18)
Log of precipitation						0.016	0.013	
						(0.92)	(1.24)	
Observations	62	62	62	62	62	62	62	62
Within R-squared	0.16	0.32	0.20	0.17	0.19	0.19	0.40	
Kleibergen–Paap rk LM statistic (p value)								8.72
								(0.01)

Table 3 (continued)

	Dependent variable: EMIGOUT_RATIO						
	OLS fixed effects						2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Kleibergen–Paap rank Wald F-statistic								12.59
Hansen J-statistics (p value)								1.65 (0.19)

The asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust t-statistics are presented in parentheses. The robust t-statistics are calculated based on standard errors adjusted for 31 clusters at the province level and are robust against heteroskedasticity and/or serial correlation in the idiosyncratic error. Stock–Yogo critical values for weak identification tests (used for Kleibergen–Paap rk Wald F statistics) are 19.93 for 10%, 11.59 for 15%, 8.75 for 20%, and 7.25 for 25% maximal IV sizes

4 Results

The results of panel fixed effects regressions are presented in Table 3. We included AOD and other possible determinants of net outmigration in each estimation. Regardless of which control variables were included in the model, the results indicated that within-province changes in AOD have the expected positive (increasing) effect on within-province changes in EMIGOUT_RATIO and are statistically significant across most specifications.

This result supports our hypothesis that provinces with higher levels of air pollution experience more net outmigration. In addition, this finding is consistent with Qin and Zhu (2018), Lu et al. (2018), and Chen et al. (2017), which showed that there is a positive relationship between pollution and actual migration or intent to migrate in China. This result also supports the theoretical work of Wolpert (1996), which argues that migration is a response to residential stressors, such as pollution and traffic congestion.

Among the control variables, the only statistically significant driver of net outmigration is real GDP per capita. Higher levels of income per capita, as a measure of economic and business opportunities in source locations, reduce net outmigration. This finding is consistent with earlier findings in the literature (e.g., Hunt 2006; Ruyssen et al. 2014). Moreover, in line with Hunt (2006), we find an insignificant relationship between unemployment rates in the place of origin and outmigration. Our regression results also show that medical facilities and precipitation levels did not play important roles in net outmigration over the study period, as the coefficients of *hospital facility* and *precipitation* are not significant (see columns 5, 6, and 7 of Table 3).

Model 7 in Table 3 includes all control variables in addition to our main variable of interest (AOD). The positive association between higher levels of air pollution and net outmigration is robust in this general specification. More specifically, a 1-unit increase in the AOD index is associated with an increase in the net outmigration ratio (normalized by the size of population) by 0.346 points. However, a 1-unit increase in the AOD index is a substantial increase, as the range of this index in our sample is 0.246 (0.409–0.163). Therefore, the difference between the maximum and minimum AOD values is approximately one-fourth of a "1-unit increase." For a more meaningful interpretation of our results, we considered the interquartile range in the AOD index (switching from the first to the third quartile of the AOD distribution, namely, from 0.23 to 0.29) and multiplied it with the estimated coefficient of AOD (0.346). Thus, a move from the 1st to the 3rd quartile of the AOD index increased the net outmigration ratio (controlling for other factors) by an estimated size of $0.34*0.06 = 0.0204$. How substantial is the estimated effect of 0.0204 on net outmigration (normalized by population)? To check, we can compare the 0.0204 increase with the interquartile ranges in EMIG_OUTRATIO $(0.01 - (-0.02) = 0.03)$. Alternatively, we can compare the estimated effect of 0.0204 with the size of the range in EMIG_OUTRATIO $(0.06 - (-0.08) = 0.14)$, which means that the estimated effect accounts for approximately 15% of the entire range of variation of the dependent variable (net outmigration ratio)

in the sample. In both cases, we can suggest a substantial effect of a within-province increase in AOD on within-province increase in net-outmigration ratio.[11]

4.1 Issue of endogeneity

The above findings are based on the panel fixed effects estimation method. As a robustness check, we re-estimated Eq. 1 using a two-stage least squares (2SLS) estimator, which is one of the most common instrumental variable estimators. The reason for employing the 2SLS estimator is to account for possible endogeneity in the model due to the likely reverse causality issue (e.g., bidirectional relationship between air pollution and outmigration). For example, we argue that local air pollution increases outmigration; however, it can be the case that increasing outmigration reduces air pollution via a decrease in the labor force and economic activity. In such cases, we may experience a simultaneous bias. To address this concern, we treated our measure of local air pollution (AOD index) as an endogenous variable and used an instrumental variable procedure to estimate the exogenous impact of AOD on the net outmigration ratio.

To instrument the AOD variable, we used province average annual temperature and the standardized precipitation-evapotranspiration index (SPEI)[12] (with larger values indicating higher degrees of moisture). We assumed that these climatic variables are exogenous to net outmigration and can affect our outcome of interest via their effects on AOD. There is evidence on weather conditions (e.g., temperature, sunlight, precipitation, wind speed, and humidity) affecting air quality (Liu et al. 2020; UCAR 2020), which supports the relevance of these instruments for the AOD index.[13]

The results of the 2SLS estimator are presented in column 8 of Table 3. In line with our findings from the fixed effect estimations, AOD is positively and significantly related to EMIGOUT_RATIO. The estimated size of the coefficient increased even after controlling for possible endogeneity of AOD. A shift from the 1st to the 3rd quartile of the AOD index increased the net outmigration ratio (controlling for other factors) by an estimated size of 0.63 * 0.06 = 0.0378. Considering the standard deviation of the net outmigration ratio in our sample (0.0287), higher air pollution based on Model 8 in Table 3 leads to an increase in net outmigration from the province by 1.3 standard deviation.

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[11] We thank the referee for raising this point.

[12] This index is used to measure drought intensity. For more information, see Farzanegan et al. (2020). It should be noted that both excluded instruments are relevant which guarantees the identification of the model. Partial R^2 of excluded instruments is 0.31. The partial R^2 statistic measures the correlation between AOD and the additional instruments after partialing out the effect of other variables. Stock et al. (2002) suggest that the F statistic should exceed 10 for inference based on the 2SLS estimator to be reliable when there is one endogenous regressor. In our case, the F statistic is 12.6. Also, the p-value for testing the relevance of the two excluded instruments for AOD is 0.0002, which confirms the relevance of both instruments. In the first-stage regression results (available upon request), both excluded instruments for AOD are statistically significant at 95% confidence interval.

[13] Also see https://www.sciencemag.org/news/2019/04/drought-not-just-about-water-it-affects-air-pollution-too.

The diagnostics also show both the relevance and validity of the employed instruments. To test the null hypothesis that excluded instruments are irrelevant (under-identification of the model), we relied on the Kleibergen–Paap rk LM statistic with a value of 8.72 and a p value of 0.01. Therefore, we can strongly reject the null hypothesis of under-identification. To examine the weak instruments issue, we used the Kleibergen–Paap rk Wald F statistic, which tests the null hypothesis that excluded instruments are weak (weak identification). The Kleibergen–Paap Wald rk F statistic (12.59) was above the 15% critical value for maximal IV size (11.50). Overall, we reject the weakness of the instruments. After gaining confidence in the relevancy condition of our instruments for AOD, we examined the exogeneity of the instruments, which is important for the validity condition. We used the Hansen J-test (Hansen 1982). The null hypothesis that the instruments are valid (i.e., they are not correlated with the error term and are correctly excluded from the equation) cannot be rejected at a 5% level of significance (p value: 0.19).

4.2 Issues of outliers

Are the results presented in Table 3 due to outliers or influential observations? To check the possible outliers or influential observations, we excluded the capital city, Tehran, from estimations and re-estimated our model, as this province has a specific position in Iran as the center of Iranian political and economic administration. As can be seen from Table 4, excluding Tehran from our sample has no significant impact on our initial observation of the positive relationship between the AOD index and EMIGOUT_RATIO.

To check the impact of outliers or influential observations (outside of Tehran) that may affect our main general specification (Model 7 of Table 3) further, we examined the residuals to identify observations with very large leverage or very large squared residuals.

We followed the procedure in Bjorvatn and Farzanegan (2013) and Farzanegan and Witthuhn (2017). Following the identification of the large residuals, we applied robust regression, which assigns lower weights to possible outliers (Hamilton 1991). Outliers are those cases that show high levels of residuals and leverage. We re-estimated Model 7 in Table 3 by using pooled ordinary least squares (OLS) with province dummy variables. Then, we used the "leverage-versus-squared-residual plot," which produces a figure that illustrates the leverage versus the squared residuals (see Fig. 4).

Following this step, we calculated Cook's D[14] and its cutoff, which is 4/62.[15] Finally, to address the possible impact of outliers, we used a robust estimator (Li 1985). Robust regression is an appropriate compromise between excluding points

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[14] Cook's distance (or Cook's D) is a measure that combines the leverage and residual information of an observation. An observation with an extreme value on a predictor variable is a point with high leverage. Leverage is a measure of how far an independent variable deviates from its mean. High leverage points can have a great effect on the estimate of regression coefficients. The residual is the difference between the predicted value (based on the regression equation) and the actual observed value. Cook's distance estimates the variations in regression coefficients after removing each observation, one by one (Cook 1977).

[15] Since Cook's distance is in the metric of an F distribution, the median point of the quantile distribution can be used as a cutoff (Bollen and Jackman 1985). A common approximation is to use 4 divided by the numbers of observations, which usually corresponds to a lower threshold (i.e., more outliers are detected).

Table 4 Panel analysis with province fixed effects without Tehran

	Dependent variable: EMIGOUT_RATIO						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
AOD index	0.212**	0.292**	0.219**	0.159	0.245**	0.218**	0.288*
	(2.10)	(2.51)	(2.34)	(1.19)	(2.55)	(2.20)	(1.83)
Log of GDP per capita		− 0.043**					− 0.038**
		(− 2.54)					(− 2.18)
Unemployment			− 0.002				− 0.002
			(− 1.35)				(− 1.48)
Gini index				0.084			0.028
				(1.02)			(0.30)
Hospital facility					0.001**		0.000
					(2.18)		(0.98)
Log of precipitation						0.018	0.018
						(1.04)	(1.50)
Observations	60	60	60	60	60	60	60
Within R-squared	0.13	0.28	0.19	0.15	0.19	0.17	0.39

The asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. Robust t-statistics are presented in parentheses. The robust t-statistics are calculated based on standard errors adjusted for 31 clusters at the province level and are robust against heteroskedasticity and/or serial correlation in the idiosyncratic error

with higher leverages or residuals entirely from the analysis and including all data points, treated equally, in OLS regression. Robust regression will assign a missing weight to observations with Cook's D larger than 1. Cases with large residuals tend to be down-weighted in robust regressions. The more cases there are in the robust regression that have weights close to one, the closer the OLS results are to the robust regressions.

The results are shown in Table 5. The robust regressions in Table 5 assign lower weights to cases with higher Cook's D indicators (those that exceed the 4/62 threshold). Since Cook's D did not exceed 1 in any of the cases, none were excluded from the robust regressions and the total number of observations remains at 62. In our sample, robust regressions assigned the lowest weights to Sistan and Baluchestan (0.075), Chaharmahal and Bakhtiari (0.076), Kohgiluyeh and Boyer-Ahmad (0.091), Hamedan (0.24) and Kermanshah (0.70).

Our main results from the robust regressions are qualitatively and quantitatively similar to the previous results.[16]

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[16] In the robust regression we use pooled OLS with province dummy variables because this method does not recognize the fixed effects estimation command. The calculated (adjusted) R squared therefore differs from the within-province R-squared presented in Tables 3 and 4. For more information on calculation of R-squared with robust regression see https://stats.oarc.ucla.edu/stata/faq/how-can-i-get-an-r2-with-robust-regression-rreg/.
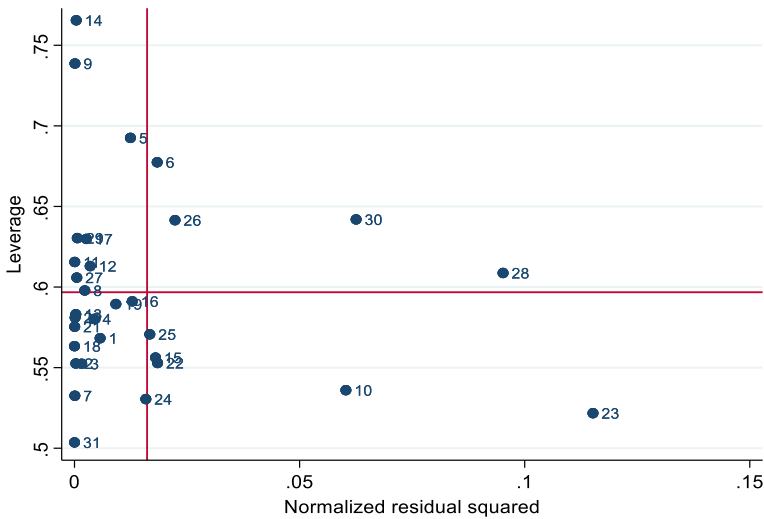
Fig. 4 Leverage versus squared residual plot. *Note*: The lines on the chart show the average values of leverage and the (normalized) residuals squared. Points above the horizontal line have higher-than-average leverage (such as code of 26 (Tehran)); points to the right of the vertical line have larger-than-average residuals (again, such as code of 26 (Tehran), code of 30 (Sistan and Baluchestan province), and code of 28 (Kohgiluyeh and Boyer-Ahmad province))

Table 5 OLS and robust regression results

	Dependent variable: EMIGOUT_RATIO	
	OLS	Robust regression
AOD index	0.346**	0.398***
	(2.94)	(3.28)
Log of GDP per capita	− 0.046**	− 0.058***
	(− 2.43)	(− 3.01)
Unemployment rate	− 0.002	− 0.002*
	(− 1.39)	(− 1.83)
Gini index	− 0.016	− 0.081
	(− 0.17)	(− 0.83)
Hospital facility	0.0001	0.0002
	(0.23)	(0.28)
Log of precipitation	0.013	0.004
	(0.82)	(0.26)
Province dummies	Yes	Yes
Observations	62	62
Adjusted R-sq	0.83	0.68

The asterisks *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. The *t*-statistics are presented in parentheses

5 Conclusion

In this study, we examined the impact of air pollution on the domestic net outmigration ratio in Iran using an aerosol optical depth index. Employing panel data from 31 Iranian provinces over two periods, 2011 and 2016, our findings suggest that higher levels of air pollution within provinces significantly increase the levels of net outmigration from the affected provinces. This increasing effect is robust while controlling for other economic and social drivers of internal migration and province fixed effects. Our panel analysis with province fixed effects OLS regression also shows that a move from the 1st to the 3rd quartile of the AOD index increases the net outmigration ratio (controlling for other factors) by 0.0204, which is equal to one standard deviation of the net outmigration ratio. The estimated effect of 0.0204 approximately equals an increase from 1st to the 3rd quartile of the net outmigration ratio.

The increasing effect of local air pollution on net outmigration becomes stronger when using the instrumental variable approach, which addresses the possible endogeneity of the AOD index. The 2SLS estimation results show that a shift from low to high pollution within a province leads to an increase in the net outmigration ratio by 1.3 standard deviation units, adjusting for other factors and province fixed effects. Among the control variables, we find that higher levels of income per capita, as a measure of economic activities and market potential, discourage internal outmigration from the provinces of Iran.

Internal migration from regions with a degrading environment to other provinces may increase the social and economic burden on the management of the receiving regions, increasing informal settlements and marginalization. By contrast, source provinces can be affected by the loss of skilled labor and an insufficient working-age population for investors who often look at the size of the market and human resources for their potential investments.

Our findings suggest that policymakers could control forced internal migration by focusing more on environmental projects and addressing the factors that contribute to the degradation of air quality (particularly within two of the most polluted provinces of Iran, Khuzestan and Sistan and Baluchestan). In addition, such investments by the government in critical provinces may also lead to higher levels of local economic activity, which may dampen internal outmigration from the province (independent of the role of AOD). Nevertheless, as shown by Gholipour and Farzanegan (2018) and Farzanegan and Markwardt (2018), the final effect of environmental expenditures by governments on pollution depends on the quality of institutions. Therefore, institutional quality (e.g., control of corruption) should be improved along with increasing government expenditures on environmental protection.

Declarations

Conflict of interest The authors declare that they have no conflicts of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Availability of data and material Data will be available upon request.

Appendix

See Table 6.

Table 6 Descriptive statistics for various quartiles of net outmigration ratio and AOD

EMIG_OUTRATIO (net outmigration ratio)

	Percentiles	Smallest		
1%	− 0.08	− 0.08		
5%	− 0.05	− 0.05		
10%	− 0.04	− 0.05	Observations	62
25%	− 0.02	− 0.05	Sum of weights	62
50%	0		Mean	− 0.004
		Largest	Std. Dev	0.029
75%	0.01	0.05		
90%	0.04	0.05	Variance	0.001
95%	0.05	0.06	Skewness	0.155
99%	0.06	0.06	Kurtosis	3.132

AOD

	Percentiles	Smallest		
1%	0.16	0.16		
5%	0.19	0.18		
10%	0.19	0.19	Observations	62
25%	0.23	0.19	Sum of weights	62
50%	0.25		Mean	0.261
		Largest	Std. Dev	0.055
75%	0.29	0.38		
90%	0.33	0.4	Variance	0.003
95%	0.38	0.4	Skewness	0.838
99%	0.41	0.41	Kurtosis	3.670

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