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Mohammad Ahmadizadeh, Amirhossein Amini and Hadi Esfahani

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Dust Storms and House Prices*

Mohammad Ahmadizadeh†
University of Illinois at Urbana-Champaign, Department of Economics

Amirhossein Amini‡†
Howard University, Department of Economics

Hadi Salehi Esfahani†
University of Illinois at Urbana-Champaign, Department of Economics

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Abstract

This paper provides new empirical evidence on the economic impact of climate change. We investigate the effect of the recent sharp rise in the number of dust storms on the housing market in Iran. We use city-level house price indices as well as a micro-level dataset of almost two million housing transactions in the Iran's housing market along the data on dust storm exposure from on-the-ground weather stations over recent decades. The regional nature of the increase in the dust storms and their significant variation across Iranian cities allow us to estimate the causal effect of dust exposure on house prices with relative accuracy. We find that the increased frequency of dust storms during the past two decades is associated with sizable and highly uneven declines in property values in many Iranian cities. This research is among the first to investigate the causal relationship between dust storms and house prices. The results have important policy implications at the national and international levels.

Keywords: Air Quality, Dust Storm, Environmental Degradation, Housing Market, Iran, MENA Region.

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† Email addresses: Ahmadiz2@illinois.edu, Amirhossein.aminibe@Howard.edu, Esfahani@illinois.edu.
‡ Corresponding author.

1 Introduction

In recent decades, concerns about the adverse economic and social consequences of environmental degradation have been growing in many parts of the world. The problem has become increasingly pressing in many low- and middle-income countries, particularly those in the Middle East and North Africa (MENA) region. Climate change has intensified the episodes of extreme temperatures and droughts that contribute to dust storms (Rotstayn et al., 2011). Poor policy making in many instances has also made matters worse. There is a clear need for better understanding of these events and their consequences, so that future trends can be better assessed, and more appropriate policies can be adopted. However, despite the importance of the issue, the body of economics research on this environmental degradation remains limited (Middleton, 2017; Jones, 2023). This paper is an attempt to contribute to that literature. It focuses on the effects of dust storms on house prices in Iran. The case offers a window onto the broader economic effects of environmental degradation.

Dust storms significantly affect life satisfaction, adult and infant health, cognitive performance, and economic activities (Lavy, Ebenstein, & Roth, 2014; Jones 2020). Dust is a combination of many fine particles, some of which are toxic. The layers of remaining dust from the storms affect agricultural activities and production. Governments can pursue policies that prevent desertification and maintain denser vegetation cover on arid lands to prevent dust particles from rising. They can also guide the formation of population and economic activity centers in ways that reduce the impact of dust storms. However, these are long-term projects and require extensive international cooperation. In the short run, governments usually try to mitigate the situation by closing businesses and limiting people's movement on dusty days. Lack of efficient measures to tackle the sudden surge in dust storms could trigger discontent and lead to political protests and conflict. This is what happened in affected areas in Iran after early 2000s when the frequency of dust storms increased dramatically.[4] Similar situations occurred in the region, including Iraq (Ahmadzai, 2023). Due to the nature of the problem, which needs international cooperation among countries, there are no effective policies yet to improve the situation.

The association between air quality and house values has been studied in many contexts. The sources of air pollution in most past studies are human industrial activities, which are largely subject to regulatory policies at the local or national government levels. Dust storms, by contrast, are typically driven by regional or global forces. In this sense, the present paper contributes to a less-studied segment of environmental economics, and our results have implications for policy at cross-national and global levels (Shepherd et al., 2016). This is particularly important for MENA countries that have been experiencing severe environmental degradation as well as major political tensions at the national and international arenas.

The case of Iran is worthwhile to examine because of the magnitude and variations of the dust storms that it has experienced. Over the past two decades, the frequency of dust storms, which are significant manifestations of environmental degradation, has grown markedly in Iran and its surrounding region (Figure 1). The average number of dusty days per year across the Iranian cities in our dataset increased from about 5 in the 1990s to close to 13 during 2000-2007 and then to about 32 in the 2008-2016 period, rising approximately two and a half times every eight years! There were also major differences across locations in the country, with the cities in the west and southwest being most affected and those in the north and east being largely spared (see Figure 2). As Figure 1

[4] See https://www.nytimes.com/2017/02/19/world/middleeast/iran-ahvaz-pollution-protests.html. The public discontent about dust storms after 2008 was also reflected in parliamentary and presidential elections. In 2013, a group of the Iranian parliament members resigned in protest to the government's inadequate response to the dust storms in western provinces of the country.

shows, the standard deviation of the number of dusty days across cities grew rapidly along the average number.

The immense rise of the number of dusty days and its variance across cities show the enormity of the problems that dust storms are posing for the country. In recent years, about two thirds of the population (more than 60 million people) have been directly affected by the storms. Incidentally, the heterogeneous rise of dusty days across cities makes the case for studying dust storms in Iran more compelling from a technical point of view: it facilitates the identification and precision of the effects of dust storms on local housing markets.

The studies of the association between air quality and housing values are typically based on hedonic price models. They seek to measure the impact of air quality as an environmental amenity on housing values. The findings are typically interpreted as estimates for the households' average marginal willingness to pay for clean air (Small, 1975; Smith & Huang, 1995). A change in air quality may affect the marginal willingness to pay for housing in each location via different channels, e.g., life satisfaction and health effects of the declining in air quality, changes in productivity and wages, and the households' costs of mitigating the effects dust storms, including migration and political action to get the government to act. The hedonic price estimates typically represent the net outcome of such effects. Our methodology follows this line of research.

Our work relies on the most comprehensive data set available for Iran's housing market. The Statistical Center of Iran (SCI) has been collecting data on samples of house sales for some decades and started forming and publishing city-level indices for a limited number of provincial capitals since early 1990s. This data was extended to all provincial capitals in 2000. Meanwhile, a new law in 2009, required all housing sales in the country to be registered online through a system managed by Iran's Ministry of Transportation and

Urban Development. The Ministry has compiled the information collected in this way into a transaction-level dataset. It makes an anonymized version of this dataset available for research purposes. This version excludes units such as single-family dwellings for which transaction parties can potentially be identified.[5] We obtained a copy of this dataset that covers all apartments sold in the country during the period 2010-2017.

For weather and dust emissions data, our sources are the Global Met Office Integrated Data Archive System Land and Marine Surface Stations data, available from the British Atmospheric Data Centre (BADC). The dataset provides a detailed weather data on an intraday basis from 86 ground stations in Iran.

We carry out the estimations using both city-level house price indices for 1993-2016 and transaction-level data for the properties sold during 2010-2017. The two datasets produce very similar estimates for the effect of dusty days on house prices. The results have important implications for the trends in the housing market, migration, civil conflicts, public policy, and political stability.

To the best of our knowledge, our paper is the first to analyze the causal impact of dust storms on housing prices. We find an increase of one dusty day per year lowers house prices by about 0.14 percent. This implies a drop of 1.1 percent in average house prices between 1990s and 2000-2008, and a further decline of 2.7 percent during 2008-2016, adding up to a total loss of about 3.8 percent in the average house values between 1990s and 2008-2016. This impact, of course, is not uniform across cities: The change in the share of dusty days (SDD), along with the implied price decrease, was much larger for western and some southwestern cities compared to those in other regions.

Our findings have important policy implications at both national and international levels.

[5] In Iran, by law, information about property transactions is private.

The estimation results show that in regions affected by droughts and desertification, such as the MENA region, dust storms may impose sizable costs on households in various forms (e.g., reduced life satisfaction, health, and productivity as well as relocation). In addition to welfare losses, such costs could cause social, political, and even international conflict, especially because they tend to be highly uneven. National governments need to investigate the causes of such storms, and to adopt policies that mitigate their adverse economic and environmental impacts. Also, since the recent rises in dust storms tend to be regional phenomena that are, at least in part, driven by the global climate change, mitigating policies often require international cooperation. The consequences of rising dust storms seem to be severe enough to justify comprehensive and long-term policies even when such measures are rather difficult and costly.

The rest of this paper is organized as follows. Section 2 offers a brief review of the literature. Section 3 provides background on the surge in the number of dust storms in Iran. Section 4 introduces the data and section 5 specifies the empirical model and the estimation strategy. Section 6 presents and discusses the results. Finally, Section 7 offers the policy implications of the finding and concludes.

2 A Brief Review of the Literature

The older generation of studies of the impact of air pollution on housing prices relied on cross-section data and OLS estimation method and often found a negative, albeit sometimes weak, effect (e.g., Ridker, 1967, and Ridker and Henning, 1967). Those studies, however, could not establish causal impact, because air pollution might be associated with other omitted factors that affect house prices through other channels. More recent studies such as Chay and Greenstone (2005), among others, have addressed the causality issue by exploiting changes in regulations (the U.S. Clean Air Act) that may be used as instrumental variables. They argue that the causal impact of air quality is stronger than what the earlier studies had claimed. Grainger (2012) used a similar instrumental variable approach to compare the effects of the variation in the level of pollution on rental versus owner-occupied housing markets. In a related, quasi-natural experiment, a study by Amini, Nafari, and Singh (2021) shows how policy induced air pollution generated by using low-quality gasoline can explain part of the differences in housing values within a city. A number of other studies investigate the impact of locally induced pollution and health risks on the housing market (e.g., Davis, 2004, 2011; Green & Gallagher, 2008).

Dust storms are not just a contemporary phenomenon. There are important historical cases that have received attention from the economists, most prominently the 1930s-era Dust Bowl in the United States. Hornbeck (2012) shows how the Dust Bowl has had persistent negative effects on agricultural activities, and has led to a permanent, relative decline in agricultural land values in more eroded counties in the U.S. Plains. Several recent papers in this line of research have investigated the migration consequences of the U.S. dust storms phenomenon; for example, Arthi (2018), Gutmann et al. (2016), Hornbeck (2023), Jones (2022, 2023), and Long and Siu (2018).

Studies of dust storms in other regions examine a variety of effects concerning health, agriculture, and general socio-economic activities. For example, in a study of the impact of dust in West Africa, Adhvaryu et al. (2024) show that the increase in dust levels is associated with an increase in infant and child mortality. Examples of such studies focusing on the Middle East region are: Ahmadzai (2023), Al-Hemoud et al. (2017), Alizadeh-Choobari & Najafi (2018), Khaniabadi et al. (2017), and MalAmiri et al. (2023). Studies that focus on the impact of dust storms on particular markets or industries are rare. One exception is Birjandi-Feriz and Yousefi (2017), which uses the ground-stations weather data that and finds that a higher exposure to dust storms reduces the productivity of industrial firms.

3 Background of Dust Storms in Iran

Dust storms are meteorological phenomena that are generated in arid areas when strong winds lift large amounts of dust particles from the ground high into the air and carry them long distances (Goudie & Middleton, 1992).[6] The dust travels like a tall and thick cloud that covers vast areas, reducing visibility and causing breathing difficulties. It may also interfere with the operation of machines. Dust storms could last from a few minutes to a few days, always leaving a layer of dust everywhere in their wake. The disruption that such storms bring to activities in their paths is one part of the economic costs that they entail. Another adverse effect is the long-term health hazards such as respiratory problems, asthma, lung cancer, and other interstitial lung diseases. These effects have important implications for the demand and supply of housing in different locations, depending on the extent of exposure to those storms. The consequences are likely to manifest themselves in relatively short times compared to other common air pollutants because dust is quite visible, and its immediate impact is very tangible.

Countries in the MENA region are part of what has been termed the "Dust Belt". Historically, the population of this region has been exposed to occasional dust and sandstorms, especially in more arid areas of the region. However, due to global climate change and human activities, the incidence of dust storms has increased throughout the MENA region in the past couple of decades. Boloorani et al. (2014) investigate the sources of the increase in dust storm frequency in Iran. They find that the main sources are located in other countries, especially Syria, Iraq and Saudi Arabia (Figure 3). Besides climate change that has brought about long-lasting droughts, a combination of political instability and negligent or adverse policies in the countries of the region have set the stage for the rise in the incidence of dust storms. Depending on the weather conditions and wind

[6] For more information about the nature and sources of dust storms as well as images that depict the situation from different perspectives, see https://scijinks.gov/dust-storm/.

direction, the dust storms travel across borders and deposit silt in vast areas, mostly in western and southwestern Iran. An increase in the number of dusty days in a polluted city significantly negatively impacts the health, productivity, and life satisfaction of its residents. These effects may also lead to outward migration from those areas.

The persistent presence of dust storms is perceived by individuals as an environmental disamenity that gets reflected in the housing market in the form of lower prices. Moreover, the externally induced nature of Iranian dust storms makes their variations largely exogenous to local factors in the country's urban housing markets. Also, the government's policy responses are unlikely to have affected the frequency and intensity of those storms because such measures have been very limited in Iran. Despite many protests by citizens and their representatives in exposed cities in Iran, the government and local authorities have thus far been unable to devise and implement effective policies to improve the situation. Given these features of the conditions in Iran, the air pollution induced by dust storms is less subject to endogeneity and omitted variables biases in the models being estimated, especially when compared with the models of air pollution caused by internal combustion engines or industrial activity. Nevertheless, in our system GMM estimation, we use GMM-style instruments to address any concern over endogeneity of the dust variable.

4 Data

Table 1 provides the information on the sources of our data. The main datasets consist of the weather and housing market data, which we discuss in this section.

4.1 Weather Data

The literature examining the impact of climate change on economic activity relies on four main sources of weather data: ground stations, gridded data, satellite measurements, and reanalysis data.[7]

Ground stations, when present and functional with sufficient spatial coverage, provide accurate and very high-quality data. However, it is not uncommon for some stations to enter and exit service occasionally. Also, the spatial coverage could be an issue, especially in low-income countries. Gridded data are derived from the interpolation of ground stations data, hence providing more spatial coverage where coverage is a problem. In the literature, gridded data method is widely used for global temperature and precipitation measurement (Auffhammer, Hsiang, Schlenker, & Sobel, 2013). An alternative is to use satellite signals to generate weather data. This method is helpful in areas with limited ground stations. However, it faces some challenges because the measurements involve inaccuracies if the satellite position changes, the instruments operate with error, the terrain is complex, or cloud cover or atmospheric contaminants interfere with the signals. The final source is reanalysis data, obtained from a combination of information from ground stations, satellite data, and other sources of information.[8]

For our study, fortunately, we have access to reliable ground station data with reasonable coverage. We obtained that data from the website of the Met Office Integrated Data Archive System (MIDAS) Land and Marine Surface Stations Data, made available by the British Atmospheric Data Centre (BADC). The dataset offers high-frequency data for more than 300 weather-related measures, covering weather conditions, wind parameters, air and soil temperatures, sunshine duration, as well as measurements of radiation, rainfall, and some other climatology indicators. The dataset covers 86 ground stations in Iranian cities. As shown in Figure 4, the stations are distributed broadly across the country. Even though some old stations have been recording weather data with low

[7] Depending on what kind of weather elements, there some other ways of weather data sources, which are mostly combinations of main four ways and mathematical computation to get more complete data see Dell et al. (2014) for more details.

[8] There are differences between gridded data and reanalysis data. see Dell et al. (2014) for more information.

frequency since the early 1950s, all the stations we use in this study provide high-frequency weather data for the years 1990-2017.

Since dust storm is a well-known weather phenomenon, there are specific codes defined in the dataset to measure dust emission. It completely distinguishes between dust emission and other forms of air pollution like fog and industrial pollution that share some characteristics, like reduced visibility, with dust storms. For dust emission from external sources, there are codes which are reported by weather stations (Shao, Klose, & Wyrwoll, 2013). These codes include a reference to widespread dust suspended in the air, not raised by wind at or near the station at the time of observation (Weather state code 06). This weather code measures dust storms from external sources. Birjandi-Feriz and Yousefi (2017) also interviewed experts at land stations from Iran's Meteorological Organization, confirming that considering the 06 weather state code is the most accurate way of measuring dust storms.

Each ground station in our dataset reports the weather data once every 3 hours. Considering the nature of dust emission, the stations data may miss very brief dust storms, but capture the storms that are longer than a couple of hours and, therefore, are likely to matter. This should not affect our results in any major way, particularly because errors in measurement are unlikely to be systematic across locations. We classify a day as a 'dusty day' if the ground station reports at least one occurrence of weather state code 06, which is primarily associated with dust, during that day. We then calculate the share of dusty days (SDD) for given periods (e.g., month, six months, or more) before the date of each transaction or city level observation. We use these shares as independent variables in regression model that determine house prices.

4.2 Housing Data

Iran's Ministry of Transportation and Urban Development has been collecting transaction-level data in the housing market since 2009, when the government made it mandatory for all housing transactions, purchase or rent, to be registered online.[9] The online registration forms require submission of data on a range of property characteristics, including price, age, size, transaction date, and address. This dataset has recently been made available to researchers after retraction of information that could identify the buyers or the sellers. For the sake of complete anonymity in this recently available data, transactions of all single-family dwellings have also been removed. Therefore, the dataset includes only apartment and condo units, for which only the apartment complex or building address is made available. The raw dataset that we received includes close to two million observations, covering most apartment sales in the country from 2010 to 2017. We were able to match 66 cities in our transaction datasets with the weather station data available to us.

Although the transaction-level dataset provides very good and detailed information on the features of the units being sold, its time span is rather short and does not cover the years when dusty days were much more limited. To check whether inclusion of earlier years may make a sizable difference in the results, we run regressions at the city level, using house price indices provided by the Statistical Center of Iran (SCI). These indices are constructed semi-annually, using a hedonic prices method, based on SCI's sample of housing transactions in the capital cities of Iran's provinces.[10] SCI had started publishing this data for 19 cities in 1993 and then expanded it to all 29 provincial capitals in 2000. Two more cities were added in 2005 after Khorasan Province was split into three. We downloaded the available data for 1993-2016 and combined it with the weather station data. Three of the cities could not be matched with any nearby weather station. As a result, our full sample consists of an unbalanced panel of 28 cities during 1993-2016.

[9] The registration of transactions started in 2009, but it was initially limited to some cities. The process was extended to all cities in the country in 2010.
[10] In post 2016 years, the frequency of these indices has become quarterly. But to be able to employ the entire length of the dataset, we use the data at the semi-annual frequency up to 2016.

To derive the real housing prices across all datasets, we adjust current prices for inflation, as measured by the consumer price index (CPI), which is available from the Central Bank of Iran.

Missing price and SDD data for some cities pose a potential problem for our city-level analysis. Among the 28 cities in the dataset, 11 have no price data for the years before 2000. In addition, two of these cities lack price data until 2005, and three other cities have missing values for single half-year periods. Among observations with available price data, the SDD missing values are mainly confined to one city, Bushehr, which has weather data for 2012-2016 only. Two other cities, Hamedan and Isfahan, have about five years of missing data, mostly before 2000. There are also four other cities with a few missing SDD information. To check whether the missing values cause any bias in the results, we form a pared-down dataset that is closer to a balanced panel by focusing on the years after 2000 and the cities that have no more than two years of missing data in that period. The result is a "trimmed" sample with 25 cities over 17 years of data (2000 to 2016).[11] This sample has 834 observations and 16 missing values associated with seven cities. Since SDD enters the model with one lag, 809 observations end up being used in the city level regressions.

We could drop the seven cities with missing data as well to make the panel fully balanced. But that would sharply reduce the number of cities in the sample, lowering the statistical power of the regression. However, it does not change the main result of our analysis.

Table 2 summarizes data from various cities, detailing the average price per square meter, the average number of dusty days, and their respective changes across three periods: the 1990s, 2000-2007, and 2008-2016, based on city-level and weather data. The last column of this table shows the calculated percentage decline in housing prices due to the

[11] The three cities that are dropped due to numerous missing values are Bushehr (missing weather data for 12 out of 17 years), Birjand (missing price data for 6 out of 17 years), and Bojnord (missing price data for 5 out of 17 years).

increased frequency of dust storms (comparing 2008-2016 to the 1990s) based on the findings of this study in each city.

Table 3 provides the descriptive statistics for the housing datasets. The first part of this table presents the summary statistics for the full and trimmed city-level datasets. The variable "L.SDD" represents the share of dusty days in the previous period (six months). The average share of dusty days for the full sample is about 5 percent. That share is higher for the trimmed sample, which focuses on the post-2000 period.

The lower part of Table 3 shows the descriptive statistics for the transaction dataset. The average housing unit size in the transaction dataset is 87.5 square meters. The average age is about 8 years, indicating that most apartments in the transactions' dataset are relatively new. On the weather side, the average SDD is about 5 percent, as in the city-level dataset.

5 Methodology

In our analysis of house price determination in Iranian cities, we initially treat the share of dusty days (SDD_{it}) in period t and city i as exogenous. The justification for this assumption is that, as we discussed in Section 3, during the years under consideration, the variations in the sources of dust storms were by and large driven by regional and global factors, and the variation of dusty days across cities depended on their geographic locations and topographic features. Nevertheless, in our system GMM estimation, we treat the dust variable as potentially endogenous to address the possible concerns in this regard. Also, to minimize the possibility of bias due to unobserved factors, we use city and time fixed effects and city-specific time trends.

5.1 City-Level Data

We start with our city-level, semi-annual data and estimate a basic fixed-effects model:

(1) $\ln P_{it} = \alpha(SDD_{it\text{-}1}) + \delta_i + \tau_t + \eta_t + \theta_{it} + \varepsilon_{it},$

where $\ln P_{it}$ is the natural log of the real house price index for city i in period t, measured in terms of millions of 2011 rials per square meter. To capture the roles of time-invariant spatial characteristics of the cities and to control for common shocks and time trends in house prices, we include in the regression a city-specific trend, θ_{it}, and city, year, and half-year fixed effects, represented by δ_i, τ_t, and η_t, respectively. The last term in equation (1), ε_{it}, is a random error.[12] $SDD_{it\text{-}1}$ is the lagged share of dusty days during the half-year just before period t. Incorporating the contemporaneous share of dusty days, SDD_{it}, or its second and third lags, $SDD_{it\text{-}2}$ and $SDD_{it\text{-}3}$, does not yield any statistically significant coefficient for those terms. Hence, we focus on the effect of *SDD* with one period lag. The parameter of interest in equation (1) is α. We use the log of the price index in equation (1) so that α represents the percentage change in the price level when the share of dusty days rises by a given amount. We estimate this equation using OLS with robust standard errors with clustering on the city.

Equation (1) assumes that the error terms are not autocorrelated and that the full effect of the SDD in each period on house prices has materialized in the following period. But, as we will see below, this hypothesis is rejected by the Wooldridge test of autocorrelation for panel-data. To address this problem, one can introduce the lagged values of the dependent and independent variables on the right-hand side of the equation until the error term is no longer autocorrelated. For example, with when one lag is sufficient to remove the autocorrelation, the relationship can be transformed into:

(2) $d\ln P_{it} = -\beta[\ln P_{it\text{-}1} - \alpha(SDD_{it\text{-}1}) - \delta_i - \tau_t - \eta_t - \theta_{it}] + \lambda d\ln P_{it\text{-}1} + \mu d(SDD_{it\text{-}1}) + \varepsilon_{it}.$

[12] We could have included a period fixed effect in place of τ_t and η_t. However, that would have sharply increased the number parameters to be estimated, which could reduce the precision of estimates without affecting the main results of the exercise. Therefore, for the sake of parsimony, we use a year fixed effect along with an indicator of the second vs. first half of the year.

In this equation, β is called the speed of adjustment. It is expected to be positive, but less than one. The expression in brackets is the deviation of $\ln P_{it\text{-}1}$ from $\alpha(SDD_{it\text{-}1}) + \delta_i + \tau_t + \eta_t + \theta_{it}$. If this expression is positive in period t, then it will lower $\ln P_{it}$ and if it is negative, it will raise $\ln P_{it}$. In either case, in the absence of shocks to *SDD* or other factors, the deviation is driven toward zero, and in the long run, $\ln P_{it\text{-}1} = \alpha(SDD_{it\text{-}1}) + \delta_i + \tau_t + \eta_t + \theta_{it}$. In other words, the expression in the bracket acts as an "error-correction term". The parameter of interest in this equation is α, which represents the long-run effect of *SDD* on the price level. If the autocorrelation in the system is of higher order than one, additional lags of the first differences may need to be added to the right-hand side of equation (2). We use two lags of the first differences to ensure absence of any autocorrelation.

A proper estimation of equation (2) addresses the autocorrelation problem present in equation (1) and, at the same time, provides an estimate of the long-run relationship between the frequency of dust storms and the log of house price index. Note that direct estimation of the parameters of the expression in the brackets requires non-linear methods. However, we can rewrite (2) in a linear form:

$$(3) \qquad d\ln P_{it} = -\beta\ln P_{it\text{-}1} + \alpha'(SDD_{it\text{-}1}) + \delta_i' + \tau_t' + \eta_t' + \theta_{it}' + \lambda d\ln P_{it\text{-}1} + \mu d(SDD_{it\text{-}1}) + \varepsilon_{it},$$

where the prime sign indicates multiplication by β; e.g., $\alpha' = \beta\alpha$. Equation (3) can be estimated linearly to obtain the estimates $\hat{\alpha}'$ and $\hat{\beta}$. We can then recover the estimate for the parameter of interest as $\hat{\alpha} = \hat{\alpha}'/\hat{\beta}$.

Estimating (2) with the OLS or standard panel methods method may solve the autocorrelation problem, but in short panels, such as ours, we may encounter a "dynamic panel bias"; that is, the city fixed effects are correlated with $\ln P_{it\text{-}1}$ causing a bias in its coefficient (Nickell, 1981). It is also possible that SDD_{it} is not fully exogenous and may need to be instrumented. To deal with this issue, we employ the system GMM method (Arellano and Bover, 1995; Blundell and Bond, 1998), specifically, Stata's *xtabond2* module al la Roodman (2009). In this method, the equation to be estimated is combined with its first-difference transform to diminish the endogeneity and inefficiency problems that each entails when the panel is short.[13] The GMM-style instruments that we use are the second and third lags of he two main variables $\ln P_{it}$ and $SDD_{it\text{-}1}$ and their lagged first differences. To avoid having too many instruments, we use the "collapse" option of *xtabond2* that reduces the set of instruments by focusing on a small number of their principal components.

5.2 Transaction-Level Data

In a second set of regressions, we employ the transaction-level dataset, which covers the 2010-2017 period. For this purpose, we follow the approach used in the recent literature on the effects of climate change on economic activities (Deschenes & Greenstone, 2007; Dell et al., 2014; Birjandi-Feriz & Yousefi, 2017; Amini et al., 2021). Our econometric model is as follows:

$$(4) \qquad \ln p_{jit} = \alpha_{sdd}(SDD_{jit}) + \beta_{age}Age_{jit} + \beta_{size}Size_{jit} + \delta_i + \tau_t + \sigma_t + \theta_{it} + \varepsilon_{jit}.$$

Since the transaction events are recorded daily, the time indicator, t, represents the transaction date, and $\ln p_{jit}$ is the natural log of the price (in millions of 2011 rials per square meter) of apartment j, transacted in city i, on date t. Age_{jit} and $Size_{jit}$ are the unit's age (in years) and size (in square meters). As in equation (1), ε_{jit} is a random error, θ_{it} is a city-specific trend, and δ_i is the city fixed effect. For time fixed effects we include two indicators, one representing the year, τ_t and the other the season, σ_t, of the transaction. The latter helps to account for the variations in demand and supply over the year. The indicator of dust storms in this equation, SDD_{jit}, is defined somewhat differently

[13] Instead of first-differencing, one can use another deviation transforms, namely, forward orthogonal deviation, which is particularly helpful when the panel sample has many gaps. Our sample has few gaps, so we employ the first-difference approach, which is more commonly used in the literature.

compared to $SDD_{it\text{-}1}$ in equation (1). SDD_{jit} is calculated for each apartment j in city i sold at date t as the share of dusty days in the certain number of months period preceding that date. α_{sdd} is the parameter of interest. In our estimations, we experimented with different specifications of this term and explored how the time frame of dust storms affect the impact on house prices. For estimating equation (4), we use OLS with robust standard errors with clustering on city.

6 Results

6.1 City-Level Regressions

Tables 4 and 5 show the results of the city-level regressions using the full and trimmed samples, respectively. The first columns of the two tables show the results of OLS estimate of equation (1) based on the two sets. The full sample yields the estimate of α as $\hat{\alpha}_F = -0.186$, while the trimmed sample generates $\hat{\alpha}_T = -0.304$. Both estimates display statistical significance, but the latter reaches a higher level of significance and has a larger absolute value. However, as mentioned in the previous section, this estimate is likely to be biased because equation (1) ignores the possibility of lagged effects and price dynamics. This omission manifests itself in the autocorrelation of regression residuals. Indeed, as the first columns of Tables 4 and 5 show, in both cases the Wooldridge test for autocorrelation in panel data rejects the null hypothesis of no first-order autocorrelation in the residual of equation (1) at the 1% level. So, we proceed with the estimation of the dynamic model in equation (3).

The second columns of Tables 4 and 5 report the results of panel fixed-effects estimations of equation (3) using the full and trimmed samples, respectively. This method addresses the autocorrelation problem of the residuals, as indicated by the reported Wooldridge tests. But it produces estimates that may be biased due to the shortness of the data panel. The estimates have larger absolute values than the corresponding OLS results derived from equation (1).

Yet, they are not very significant. As Table 4 shows, for the full sample we find $\hat{\beta}_F$= 0.393 and $\hat{\alpha}'_F$ = –0.111, implying $\hat{\alpha}_F$ = –0.283. The trimmed sample generates somewhat stronger fixed-effects results, as reported in the second column of Table 5: $\hat{\beta}_T$= 0.453 and $\hat{\alpha}'_T$ = –0.185 implying $\hat{\alpha}_T$ = –0.409, which is significant, but only marginally.

The third columns of Tables 4 and 5 show the results of applying the system GMM method to estimate equation (3), using the full and trimmed samples. Both estimations meet the requirements of diagnostic tests for absence of overidentification and second-order autocorrelation, AR(2). Absence of the first-order autocorrelation, AR(1), is rejected. But, that is not a problem since it happens by construction in system GMM estimation. The procedure did not produce tests of exogeneity of instruments because the collapse option of *xtabond2* method did not yield enough instruments for the test.

The outcomes of system GMM estimation show that addressing the biases in the OLS and the fixed-effects methods raises the magnitude and significance levels of the estimates. According to Table 4, under the system GMM estimation the full sample yields: $\hat{\beta}_F$= 0.393, $\hat{\alpha}'_F$ = –0.186, and $\hat{\alpha}_F$ = –0.472, which is significant at the 5 percent level. Using the trimmed sample in Table 5 strengthens the results to $\hat{\beta}_T$= 0.425, $\hat{\alpha}'_T$ = –0.228, and $\hat{\alpha}_T$ = –0.536 with a significance level of less than 1 percent.

We will examine the implications of these findings after discussing the estimation results of the transaction-level regressions and comparing them with the results in this section.

6.2 Transaction-Level Regressions

Table 6 presents the results of estimating equation (4) with the transaction level data. We start with SDD_{jit} defined as the share of dusty days during the 12 months preceding each transaction. The first column in the table shows that the estimated coefficients of SDD_{jit} and apartment size and age are all highly significant. As one expects, the price per square meter rises with the apartment's size and declines with its age and the frequency of dust storms. The estimated value of the SDD effect on price is $\hat{\alpha}_{sdd}$ = −0.495, which is in the neighborhood of the long-run price effects found in the city-level regressions data using the system GMM method with full and trimmed datasets. This confirms those results and strengthens the case for our main finding of large negative effects of dust storms on house prices.

The above measure of dusty days does not distinguish between dusty days that occurred just before the transaction and the ones that happened months earlier. To explore whether the effect of dusty days depends on the time when they occur before a transaction, we first break up the year-long SDD into two six-months periods and form a SDD for the first six month and another SDD for the 6 to 12 months before the transaction. The second column of Table 6 shows the results when the year-long SDD is replaced by the two six-months measures. Three facts are noticeable about these results. First, the estimated coefficients of six-months SDDs are both highly significant. Second, the effect of the first six months SDD is much larger than that of the second six months (by a statistically significant factor of more than 1.8). Therefore, dusty days closer to the time of transaction have much stronger effects on house prices. Indeed, including an additional SDD variable in the regression for the third six-month period before the transaction does not yield a statistically significant effect. Hence, we only need to focus on the SDD in the 12-months period before the transaction. Third, the sum of the two coefficients of the two SDDs, −0.507, is approximately equal to the estimated coefficient of the year-long SDD in the first column, −0.495. In other words, the SDD effects seem to be additive. These observations can be further confirmed by introducing the SDD for shorter durations. For example, the third column of Table 6 shows the result of including SDDs for the first three months, second three months and 6-12 months periods, and the fourth column breaks down the first three months into the first month and the 2-3 months SDDs. In both cases, the estimates are significant, the per month effects are declining, and they add up to −0.511 and

–0.514, respectively. Clearly, these are in the mid-range of the long-run effects we found in the case of full and trimmed city-level datasets.

In the rest of this section, we assess the economic magnitude of our findings for the effect of dusty days on house prices. For this purpose, we focus on the average of the long-run effects estimated using different datasets and our preferred methods for each. The result is –0.51.

6.3 Discussion of the Economic Significance of the Results

Note that an increase of one dusty day per year raises the SDD by 1/365 and lowers house prices by 0.51/365 = 0.14 percent. This implies a decline of about 1.1 percent in average house prices for affected cities in Iran in 2000-2007 compared to the 1990s as a result of the 8-day increase (from 5 to 13) in the average dusty days per year between those periods. The further 19-day increase in the average dusty days per year in 2008-2016 compared to the previous 8 years must have had an even more dramatic effect for affected cities, lowering average house prices by an additional 2.7 percent. Thus, the total decline in the average housing price must have reached 3.8 percent.

This impact, of course, is not uniform across cities: The change in SDD between 1990s and 2008-2016 was much larger for western and some central cities compared to those in other regions. The biggest dusty day increases belong to the western cities of Ahvaz, Ilam, and Khorramabad (72 days, 66 days, and 63 days per year, respectively), which translates into price declines of 10.1 percent, 9.3 percent, and 8.8 percent, respectively.[14] The corresponding price changes in many cities in the northern and eastern regions were less than 0.5 percent. These numbers indicate huge losses to the property wealth and

[14] The city of Ahvaz, a major city of 1.4 million people in southwestern Iran, has fared particularly badly throughout this period. In March 2016, a series of unprecedented dust storms devastated the city by inundating it with an estimated 76,500 tons of dust that contained high concentration of dangerous particles, such as sulfate and sulfur. https://financialtribune.com/articles/environment/61052/76000-tons-of-dust-sand-descend-on-ahvaz.

welfare of the people who were exposed to intensified dust storms in Iranian cities.

7 Conclusion

There is a growing concern that environmental degradation is having a wide range of adverse ramifications for many parts of the world, including conflict, health, migration, and general economic activities and conditions. In this paper, we assessed the impact of growing dust storms on housing prices in Iran as a window into an important repercussion of environmental degradation. This case is interesting and useful to study because there is reliable data on dust storms and house prices in Iran with wide variation over time and across the country. In addition, the main sources of changes in dust storms seem to be regional, which could be viewed as largely exogenous for Iranian cities because the phenomenon that has remained largely unaddressed due to lack of initiative on the part of Iranian government and major strains in international relations in the Middle East. However, in our system GMM regressions, we allow for the possibility of endogeneity of the dust variable and instrument it, so that the estimates of the storm effects can be treated as causal. The extent of change in the frequency of dust storms across cities has varied greatly because the main source of dust has been to the west of Iran, and there is a high mountain range that impedes the spread of storms to the eastern and northern parts of the country.

We used two datasets, one at the city level and the other at the transaction level, to study the impact of dust storms. The results were remarkably similar. The estimates indicate that an increase of one dusty day per year on average lowers house prices by about 0.14 percent, which is by no means trivial. It implies that the average increase of about 27 days per year in dusty days between 1990s and 2008-2016 must have cost the Iranian economy 3.8 percent of its housing stock. We also find that the distribution of the costs is highly uneven across cities, some in the southwest losing about 10 percent of their housing values, while others in the north and east remaining by and large unaffected.

The losses in property values found here, of course, do not fully reflect the overall adverse economic and health effects of dust storms in the country. According to recent studies, the storms have also impacted firm and labor productivity, human health, and mortality. The government has tried some limited policies to mitigate the situation. But there is little evidence showing the number of dusty days has decreased in tangible ways.

It is known that global warming has an unequal impact on different regions of the world. For MENA countries, the emerging impacts of climate change are severe, bringing longer-lasting droughts and dust storms of greater frequency and severity. These changes can have profound consequences in the context of political stability and domestic and international conflicts. Such conflicts in turn make it more difficult for governments to design and implement effective policies that require cooperation and coordination among many political actors. Continuation of the environmental degradation crises in the MENA region can have serious socio-political spill-over effects on other regions, causing wider conflicts and massive refugee crises. In these respects, this paper highlights the important aspects of environmental degradation as a subject that warrants greater attention from economists and policy makers. Although this paper focuses on the housing markets, there are other important effects that require assessment and should be the subject of future investigations.

8 References

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Table 1: Sources of Data

Data	Source	Observation level	Frequency	Time span
Weather data	Met Office Integrated Data Archive System (MIDAS)	Weather Stations	Every 3 hours	1990-2017
Housing transaction data	Iran's Ministry of Transportation and Urban Development	Individual Transactions	Transaction	2010-2017
Average house price data	Statistical Center of Iran	Provincial Capitals	Semi annual	1993-2016
CPI	The Central Bank of Iran	Country	Semi annual	1993-2016

Note: This table explains the sources of dataset along with some information on geographical level, frequencies etc., that we use in the paper. The weather data is obtained from the global Met Office Integrated Data Archive System Land and Marine Surface Stations data, available from the British Atmospheric Data Centre (BADC), which is available (limited access) on http://catalogue.ceda.ac.uk/uuid/220a65615218d5c9cc9e4785a3234bd0.

Table 2: Trends in Dust Storms and Property Prices Across Various Cities in Iran

City Name	Ave. Annual Number of Dust Days in 1990s	Ave. Annual Number of Dust Days from 2000 to 2007	Ave. Annual Number of Dust Days from 2008 to 2016	Ave. Property Price per SqM (Millions of 2011 Rials) in 1990s	Ave. Property Price per SqM (Millions of 2011 Rials) from 2000 to 2007	Ave. Property Price per SqM (Millions of 2011 Rials) from 2000 to 2007	Change in the Number of Dusty Days from the 1990s to 2000-2007	Change in the Number of Dusty Days from t000-2007 to 2008-2016	Change in the Number of Dusty Days from the 1990s to 2008-2016	Implied Decrease in Average Property Prices (Percent)
Ahvaz	22.71	64.75	94.89	41.42	80.70	59.99	42.04	30.14	72.17	10.08
Arak	1.86	11.00	61.22	31.94	69.34	87.52	9.14	50.22	59.37	8.29
Ardabil	0.29	0.25	3.44	33.24	51.87	54.61	-0.04	3.19	3.16	0.44
Bandar Abbas	9.14	25.00	4.33		73.89	64.73	15.86	-20.67	-4.81	-0.67
Birjand	1.14	4.13	11.33		95.26	40.30	2.98	7.21	10.19	1.42
Bojnourd	0.00	0.50	2.89		94.13	53.00	0.50	2.39	2.89	0.40
Boushehr			28.00		80.30	57.56	0.00	28.00	28.00	3.91
Ghazvin	2.33	2.25	10.33	55.40	89.83	80.24	-0.08	8.08	8.00	1.12
Gorgan	0.67	0.63	2.33	37.80	58.86	57.40	-0.04	1.71	1.67	0.23
Hamedan	2.50	9.25	37.89	34.81	68.72	70.78	6.75	28.64	35.39	4.94
Ilam	6.25	15.33	72.56		54.94	39.77	9.08	57.22	66.31	9.26
Isfahan	0.33	2.17	41.33	55.71	91.01	95.54	1.83	39.17	41.00	5.73
Kerman	3.43	6.00	7.78	34.24	55.66	43.76	2.57	1.78	4.35	0.61
Kermanshah	12.57	20.38	66.89	32.95	57.03	57.47	7.80	46.51	54.32	7.59
Khorramabad	5.14	24.00	68.22		61.79	42.62	18.86	44.22	63.08	8.81
Mashhad	3.14	2.38	3.56	44.38	76.44	71.75	-0.77	1.18	0.41	0.06
Rasht	0.14	0.00	1.44	55.46	74.68	67.11	-0.14	1.44	1.30	0.18
Sannandaj	3.33	18.13	54.89		63.30	60.78	14.79	36.76	51.56	7.20
Semnan	0.83	0.13	5.22		73.19	61.83	-0.71	5.10	4.39	0.61
Shahrekord	1.00	6.38	28.78		60.17	54.54	5.38	22.40	27.78	3.88
Shiraz	16.29	37.88	66.11	56.75	77.78	76.55	21.59	28.24	49.83	6.96
Tabriz	2.00	6.75	34.56	47.72	69.04	77.78	4.75	27.81	32.56	4.55
Tehran	1.71	1.13	4.78	52.30	135.76	215.14	-0.59	3.65	3.06	0.43
Urmia	0.43	2.75	24.00	31.40	46.60	47.98	2.32	21.25	23.57	3.29
Yasuj	0.57	4.50	50.44		53.96	26.50	3.93	45.94	49.87	6.97
Yazd	12.14	18.75	45.11	33.77	42.90	40.87	6.61	26.36	32.97	4.61
Zahedan	6.43	59.63	28.44	35.42	51.25	42.18	53.20	-31.18	22.02	3.08
Zanjan	3.29	1.50	14.89	36.32	71.87	67.97	-1.79	13.39	11.60	1.62

Note: This table shows the trends in the average annual number of dusty days and the average property prices per square meter (millions of 2011 Iranian Rials) during three periods: the 1990s, 2000 to 2007, and 2008 to 2016. It also highlights the changes between each pair of periods. The last column represents the calculated percentage decline in housing prices as a result of the increased frequency of dust storms (comparing 2008-2016 to the 1990s) in each city.

Table 3: Descriptive Statistics, City Level and Transaction Level Data

	N. of Observations	Mean	St. Dev.	Min	Max
Part 1: City Level Data- Full					
Ln Price/SqM (Capitals of the Provinces 1993-2016)	1092	1.714	0.4553	0.2518	3.4576
L.Share of Dusty Days	1092	0.0538	0.0907	0	0.6066
Part 1: City Level Data- Trimmed					
Ln Price/SqM (Capitals of the Provinces 2000-2016)	809	1.8177	0.4543	0.2518	3.4576
L.Share of Dusty Days	809	0.0668	0.1003	0	0.6066
Part 2: Housing Transaction Level Data					
Ln Price/SqM (All Transactions 2010-2017)	1,792,786	2.4836	0.5533	0.7635	3.5522
SDD - 1 Month	1,792,786	0.0487	0.1089	0	1
SDD - 2-3 Months	1,792,786	0.0494	0.1	0	0.8361
SDD - 3 Months	1,792,786	0.0491	0.0946	0	0.6593
SDD - 3-6 Months	1,792,786	0.0524	0.0981	0	0.6593
SDD - 6 Months	1,792,786	0.0508	0.0825	0	0.5385
SDD - 6-12 Months	1,792,786	0.0558	0.0891	0	0.6099
SDD - 12 Months	1,792,786	0.0531	0.071	0	0.4274
Age (years)	1,792,786	8.0369	7.8224	0	70
Size (SqM)	1,792,786	87.487	35.265	20	500

Note: This table reports the descriptive statistics for both full and trimmed city-level data (Part 1) and the transaction-level data (Part 2). The variable "Ln Price/SqM" represents the logarithm of real prices per square meter for the capitals of provinces, estimated every six months from 1993 to 2016 in Part 1 and the logarithm of real prices per square meter for individual transactions in Part 2. "L.Share of Dusty Days" indicates the share of dusty days in the previous observation period. "SDD" describes the share of dusty days for a specific period before each housing transaction date.

Table 4: Regression Results for City-Level House Price Index and the Share of Dusty Days: Full Sample, 1993-2016

	(1)	(2)	(3)
	Ln Price/SqM	D.Ln Price/SqM	D.Ln Price/SqM
L.Ln Price/SqM ($-\beta$)		-0.393^{***}	-0.393^{***}
		(0.036)	(0.041)
L.Share of Dusty Days (α')		−0.111	-0.186^{**}
		(0.084)	(0.091)
LD.Ln Price/SqM (λ)		−0.022	0.025
		(0.038)	(0.075)
LD.Share of Dusty Days (μ)		−0.017	0.007
		(0.058)	(0.056)
L.Share of Dusty Days (α)	-0.186^{**}	−0.283	-0.472^{**}
	(0.075)	(0.214)	(0.237)
City Fixed Effects	Yes	Yes	Yes
City-Specific Trends	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Half Year Fixed Effects	Yes	Yes	Yes
Observations	1,092	1,037	1,037
R^2	0.932	0.442	
Adjusted R^2	0.926	0.411	
Arellano-Bond Test for AR(1) in First Differences			0.000
Arellano-Bond test for AR(2) in First Differences			0.199
Sargan Test of Overid. Restrictions			0.579
Hansen Test of Overid. Restrictions			1.000

Standard errors are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports three models for our full sample. The first column shows the results of OLS estimate of equation (1). The second column reports the results of panel fixed-effects estimations of equation (3). The third column shows the results of applying the system GMM method to estimate equation (3). System GMM diagnostic statistics p-values for the last column are provided at the bottom of the table.

Table 5: Regression Results for City-Level House Price Index and the Share of Dusty Days: Trimmed Sample, 2000-2016

	(1)	(2)	(3)
	Ln Price/SqM	D.Ln Price/SqM	D.Ln Price/SqM
L.Ln Price/SqM ($-\beta$)		-0.453^{***}	-0.425^{***}
		(0.040)	(0.045)
L.Share of Dusty Days (α')		-0.185^{*}	-0.228^{***}
		(0.094)	(0.082)
LD.Ln Price/SqM (λ)		−0.008	−0.039
		(0.038)	(0.075)
LD.Share of Dusty Days (μ)		−0.017	0.007
		(0.058)	(0.056)
L.Share of Dusty Days (α)	-0.304^{***}	-0.409^{*}	-0.536^{***}
	(0.085)	(0.214)	(0.197)
City Fixed Effects	Yes	Yes	Yes
City-Specific Trends	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Half Year Fixed Effects	Yes	Yes	Yes
Observations	809	774	774
R^2	0.935	0.469	
Adjusted R^2	0.929	0.437	
Arellano-Bond Test for AR(1) in First Differences			0.000
Arellano-Bond Test for AR(2) in First Differences			0.620
Sargan Test of Overid. Restrictions			0.336
Hansen Test of Overid. Restrictions			1.000

Standard errors are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table reports three models for our trimmed sample. The first column shows the results of OLS estimate of equation (1). The second column reports the results of panel fixed-effects estimations of equation (3). The third column shows the results of applying the system GMM method to estimate equation (3). System GMM diagnostic statistics p-values for the last column are provided at the bottom of the table.

Table 6: Regression Results for Transaction-Level House Prices and the Share of Dusty Days

	(1) Ln Price/SqM	(2) Ln Price/SqM	(3) Ln Price/SqM	(4) Ln Price/SqM
SDD - 1 Month				-0.0716***
				(0.0227)
SDD - 2-3 Months				-0.1171***
				(0.0351)
SDD - 3 Months			-0.1893***	
			(0.0572)	
SDD - 3-6 Months			-0.1391***	-0.1435***
			(0.039)	(0.0409)
SDD - 6 Months		-0.3263***		
		(0.092)		
SDD - 6-12 Months		-0.1808**	-0.1826**	-0.1817**
		(0.0703)	(0.0710)	(0.0704)
SDD - 12 Months	-0.4953***			
	(0.1599)			
Age (Decades)	-0.0060***	-0.0060***	-0.0060***	-0.0060***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Size (100s of SqM)	0.0029***	0.0029***	0.0029***	0.0029***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
City Fixed Effects	Yes	Yes	Yes	Yes
City-Specific Trends	Yes	Yes	Yes	Yes
Year Fixed Effect	Yes	Yes	Yes	Yes
Season Fixed Effect	Yes	Yes	Yes	Yes
Observations	1,792,786	1,792,786	1,792,786	1,792,786
Adjusted R^2	0.508	0.508	0.508	0.508

Standard errors are shown in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: This table presents the results of estimating equation (4) with the transaction level data. SDD shows the share of dusty days in specified periods before the time of transaction. All models include age and the size of the housing unit. Robust standard errors are adjusted for clustering at the city level.

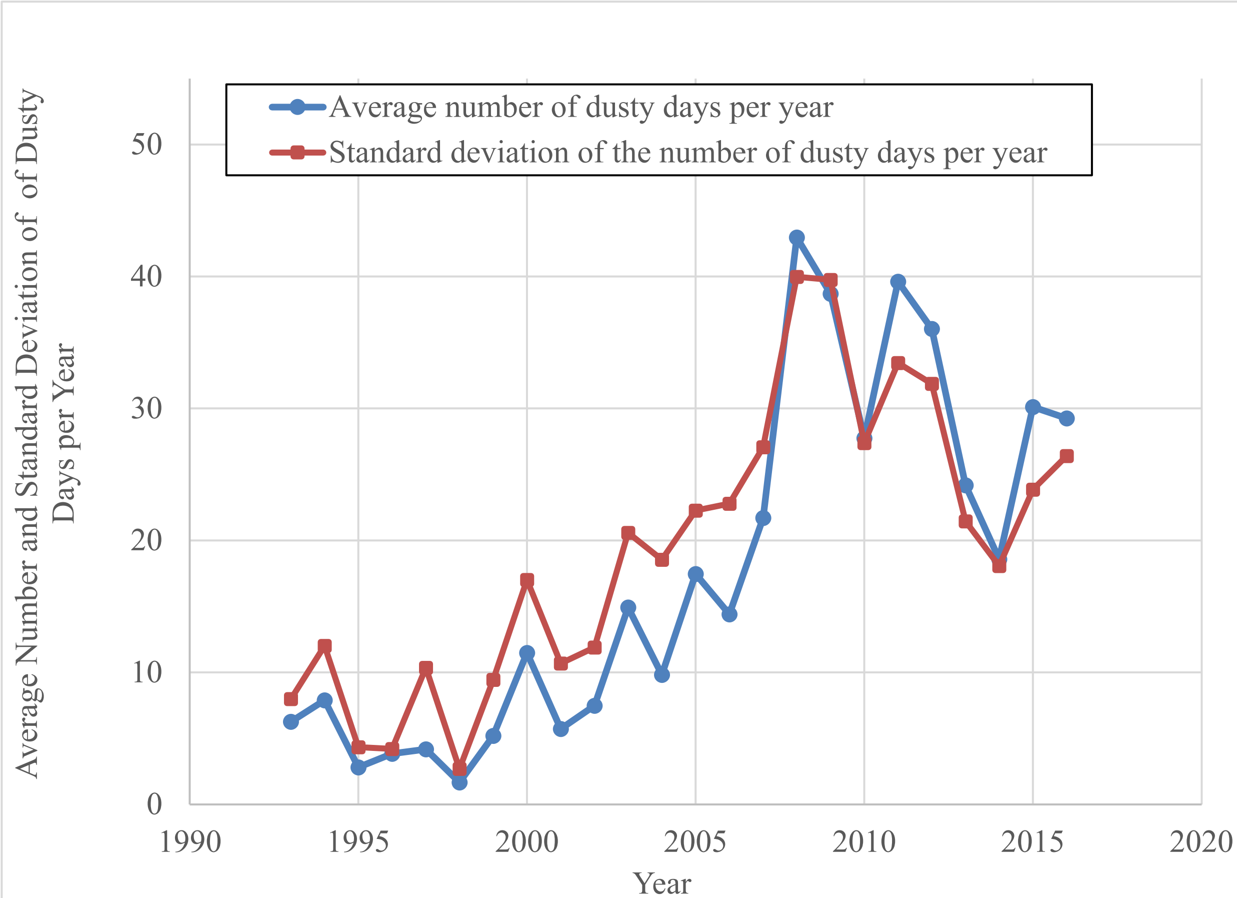

Figure 1: Average Annual Number of Dusty Days Across Iran's Provincial Capitals

Note: The figure shows that since the 2000s and the average annual number and standard deviation of dusty days across Iran's provincial capitals have increased markedly.

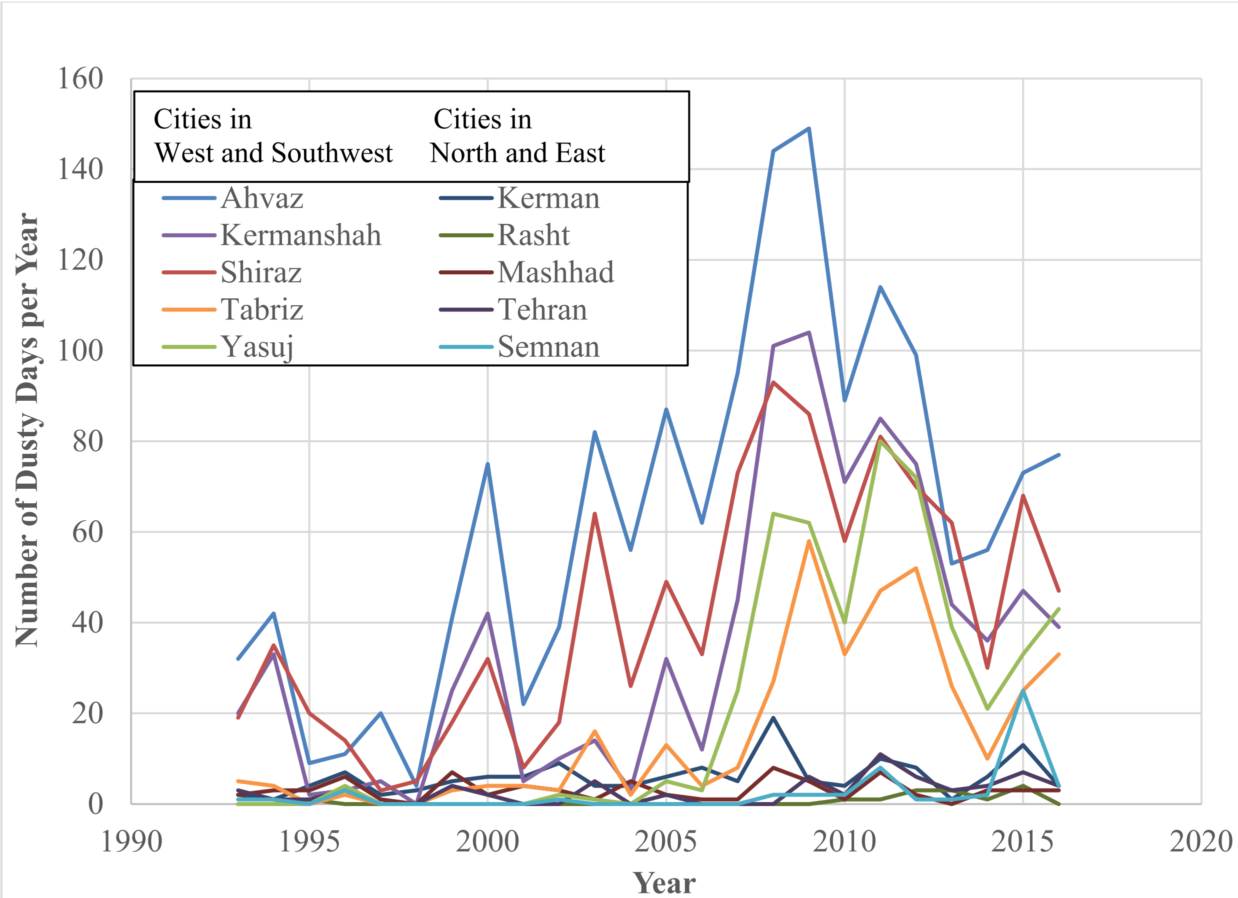

Figure 2: Annual Number of Dusty Days in Selected Provincial Capitals

Note: This figure provides examples showing that the increase in the frequency of dusty days in recent decades has varied greatly across Iranian provincial capitals, some mostly in the west and southwest experiencing sharp rises, while others mostly in the north and east experiencing barely any increase.

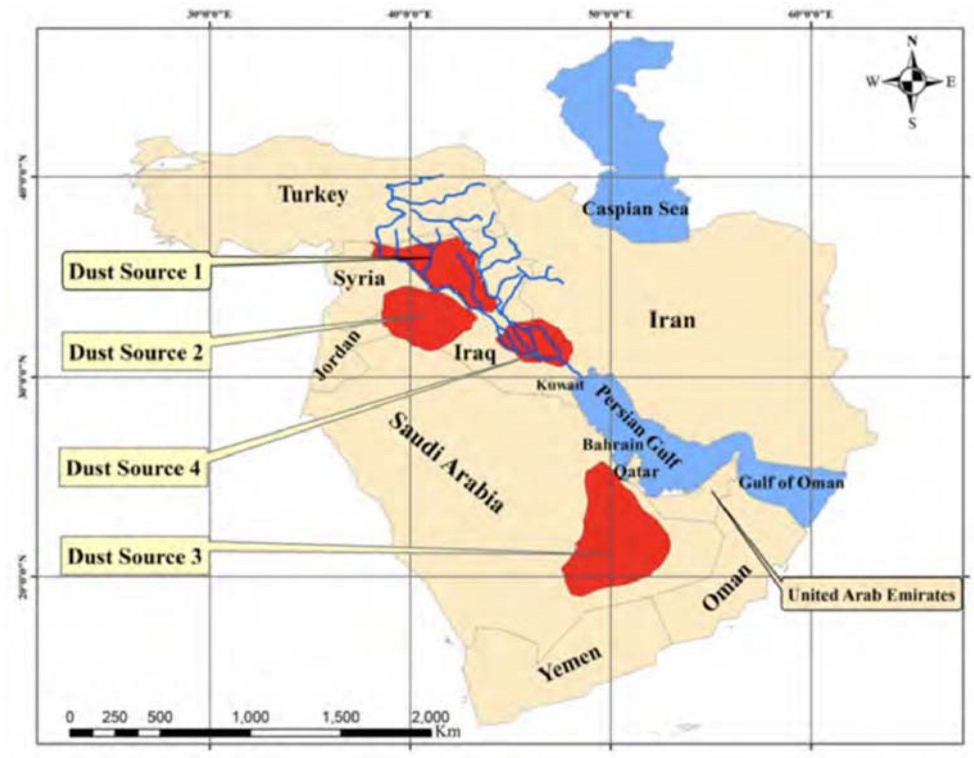

Figure 3: The Sources of Recent Dust Storm in Iran.

Note: This map shows the sources dust storms in Iran. These sources play different partial roles in number of dust storms in Iran.

Source: Boloorani et al. (2014).

Figure 4: The Ground Weather Stations Used in This Paper.

Note: This map shows the geographic distribution of weather stations from which our weather data is obtained. As observed, the stations cover various locations throughout Iran very well.

Source: Met Office Integrated Data Archive System (MIDAS) land and marine surface stations data (1853-current). NCAS British Atmospheric Data Centre.