Pouya Arab

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Education

Carnegie Mellon University Aug, 2024 – May, 2030
Doctor of Philosophy in Economics and Public Policy *Pittsburgh, United States*

Sharif University of Technology Sep, 2020 – Sep, 2023
Master of Science in Economics *Tehran, Iran*
- GPA: 17.68/20 (4/4), via 40 credits
- Master Thesis: Climate Change and Mortality: Evidence from Iran

Sharif University of Technology Sep, 2015 – Sep, 2020
Bachelor of Science in Mechanical Engineering and Minor in Economics *Tehran, Iran*
- GPA: 17.40/20 (3.77/4), via 162 credits

Research Interests

Environmental Economics, Natural Resource Economics, Experimental Economics

Research Experience

Master Thesis: Climate Change and Mortality: Evidence from Iran Sep, 2021 – July, 2023
Supervisor: Dr. M. Vesal

Research Assistant, Data Analysis Center of the GSME Aug, 2022 – Dec, 2023
Supervisors: Dr. M. Vesal
- Collecting, analysis, and visualization of climate data to provide reports on climate change in Iran

Research Assistant: Digitization to Enhance Tax Compliance in Iran Nov, 2020 – Sep, 2021
Supervisor: Dr. M. Vesal
- Reporting a comprehensive literature review on the role of digitization in improving tax compliance

B.Sc. Project: Regulatory Focus' Role in Health-Related Advertisement Feb, 2019 – Aug, 2020
Supervisor: Dr. A. Nourani, Dr. R. Hendijani

Working Papers

Climate Change and Mortality: Evidence from Iran; Joint work with M. Vesal, Available here.

Teaching Experience

Teaching Assistant in Graduate Courses: Environmental Economics, Energy Economics, System Dynamics
Teaching Assistant in Undergraduate Courses: Macroeconomics, Microeconomics, Principles of Economics, Statistics and Probability

Work Experience

Project Analyst Feb, 2018 – Jan, 2020
Rahbord Danesh Pouya Institute (RDPI) *Tehran, Iran*
- Supported various tasks in the national master planning of Iran's development, focused on the environment, resources, and social welfare.
- Facilitated several Value Engineering study workshops, such as: Drinking water supply for Ghaemshahr city based on the environmental, social, and economic assessment of the Casillian dam.

Specialized Skills

Programming & Software Tools: R, MATLAB, Stata, Julia, Python, C++, SPSS, and LaTeX
Languages: Farsi (Native), English (Fluent), Arabic (Elementary), and Spanish (Elementary)
Soft Skills: Research, Leadership, Public Speaking, and Teamwork

Test Scores

TOEFL iBT: 99/120 (Reading: 27, Listening: 25, Speaking: 23, Writing: 24)
GRE: Verbal Reasoning: 145/170, Quantitative Reasoning: 167/170, Analytical Writing: 4/6
Duolingo: 135/160 (Literacy: 135, Comprehension: 145, Conversation: 125, Production: 105)
CEFR: Level C1, after participation in an intensive English course of six weeks' duration at *Eurocentres Cape Town* in South Africa.

Awards & Honors

Ranked 43rd, Among More Than 5,000 Participants 2020
Graduate National University Entrance Exam

Winner of The Extracurricular Activities Award 2019
Student Affairs Administration of the Mechanical Engineering Department at SUT

Granted Full Scholarship for Several *TeIAS* Summer Schools 2018, 2019
Tehran Institute of Advanced Studies (TeIAS)
- Summer schools are: International Trade, Economics of Cryptocurrencies, and Big Data Economics

Ranked Top 1%, 436th, Among More Than 180,000 Participants 2015
Undergraduate National University Entrance Exam

Voluntary Experience

Sharif Economics Academic Association Aug, 2021 – Aug, 2022
Member of The Board Director, Sharif University of Technology
- Arranged several economic and environmental presentations and seminars.

Sharif Mountaineering Club Counsel Oct, 2019 – Sep, 2021
President of The Board Director

***Daad* Student Publication** Oct, 2018 – Dec, 2019
Member of The Editorial Board in Economics and Environment

Mechanical Engineering Academic Association Student Chapter June, 2017 – June, 2018
Member of The Board Director, Sharif University of Technology
- Editor-in-Chief of *Khamesh*; a student magazine in the department

Extracurricular Activities

Member of *Chakad* Orchestra (Saxophonist)
Mountain Climbing Team Leader, Climbing Mount *Damavand*, The Highest Peak in Iran
Tennis Player

Carnegie Mellon University

Cover Letter

Dear Workshop Organizers,

I am writing to express my strong interest in participating in the PhD Student Workshop on Climate Finance hosted by the NBER. I am currently a second-year PhD student in Economics and Public Policy at Carnegie Mellon University, jointly affiliated with the Heinz College and the Tepper School of Business. My research lies at the intersection of climate risk, financial markets, and public policy, with a particular focus on environmental economics.

One of my current projects, titled "Burning Signals: Wildfire and Beliefs", investigates how the disclosure of California's Fire Hazard Severity Zone (FHSZ) maps affects housing markets and mortgage contracts. This research develops a search-and-matching model with heterogeneous beliefs between borrowers and lenders, introducing the timing of public hazard disclosures as a novel determinant of default behavior. Empirically, I exploit the 2007 CAL FIRE policy reform using a staggered Difference-in-Differences framework and interact it with climate belief measures at the county level. This project aligns directly with the themes of the workshop and offers insights into how climate risk perception shapes real estate and financial decisions. Even though it is at its very early stages, a raw and preliminary draft of this work is attached for your consideration.

In addition, I have recently completed a study titled "Climate Change and Mortality: Evidence from Iran", which estimates the health impacts of temperature fluctuations across demographic groups using high-frequency mortality data. This paper contributes to the emerging literature on climate adaptation in developing countries and has provided me with a strong empirical foundation in environmental health and econometric modeling.

At Carnegie Mellon, I am an active member of the Environmental Economics Research Group, working closely with Professors Karen Clay, Nicholas Muller, Akshaya Jha, and Edson Severnini. I expect to graduate in 2030 and am eager to engage with other scholars at the workshop to receive feedback on my work and to build collaborations in the growing field of climate finance.

Thank you for considering my application. I am enthusiastic about the opportunity to present and discuss my research in this intellectually stimulating environment. Please find my CV and research paper attached.

Sincerely,

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Burning Signals: Wildfire and Beliefs Theory and Evidence*
Working Paper

Pouya Arab† Golnaz Bahrami‡

August 8, 2025

Abstract

As climate-driven wildfires intensify, their economic footprint on real estate markets becomes increasingly urgent to understand. This paper investigates the impact of wildfire risk, captured through fire-hazard severity zone (FHSZ) maps, and public-hazard disclosures on housing market dynamics and belief formation surrounding climate risks. Building on a search-and-matching model with heterogeneous borrower and lender beliefs, we extend prior frameworks by introducing a novel mechanism: the timing of public hazard disclosure as a determinant of optimal default behavior. Empirically, we exploit the 2007 FHSZ policy reform in California using staggered Difference-in-Difference (DiD) and belief-interacted panel regressions to estimate housing price, mortgage uptake, and maturity responses.

Keywords: Real Estate, Wildfire, Finance, Climate Risk Perception, Hedonic Price Model

JEL Codes: R31, R32

*We acknowledge Califonia Fire Department for their collaboration in this research project, providing information and data on Fire Hazard Severity Zone maps. We thank Karen Clay, Edson Severnini, Akshaya Jha, and Nicholas Muller for their helpful guidence and suggestions.

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1 Introduction and Motivation

In January 2025, wildfires destroyed more than 14,000 homes in Los Angeles, accounting for 17% of all properties in the Palisades and Eaton areas (Realting News, 2025). As climate risks escalate, understanding their effect on housing markets becomes urgent. Since climate change increase wildfires in terms of intensity and frequency (IPCC, 2021), real estate, the largest asset in houshold's portfolio (Davis and Nieuwerburgh, 2015), is especially vulnerable. This research aims to explore how wildfire risk and public hazard disclosures affect housing markets and belief formation about climate risks using hedonic framework.

Although much of the existing "climate finance" literature has focused on floods and sea level rise (SLR), wildfires remain under-studies despite their growing relevance (Jerch et al., 2023; Gibson and Mullins, 2020; and Hino and Burke, 2021). Additionally, there is limited research on mechanisms explaining the effects of agents' belief (e.g., being pessimistic or optimistic about climate change) on leveraging risky assets. This project aims to investigate the effects of fire hazard severity zones (FHSZ) maps on the household market while exploring different mechanisms such as cash flow restriction and income effect and Bayesian belief updating in addition to existing ones (e.g., default cost (Bakkensen and Barrage, 2017), and strategic default (Bakkensen et al., 2023)).

2 Theoretical Framework

The general setup of the model consists of a competitive search and matching model among lenders and borrowers with heterogeneous beliefs following the work of Bakkensen et al., 2023 and Geanakoplos, 2010 where borrower finds the optimal default time $\tau \in [0, +\infty)$ maximizing her value function as following:

$$V_\lambda(\mathbf{m}) = \max_\tau \mathbb{E}_\lambda \left[\underbrace{\int_0^{\tau \wedge T_\mu} re^{-rt}(h_t - b)\,\mathrm{d}t}_{\text{value of repaying until } \tau \wedge T_\mu} + e^{-r(\tau \wedge T_\mu)} \left(\begin{array}{c} \underbrace{\mathbf{1}_{\tau > T_\mu} \int_0^\infty re^{-rt} h_{t+T_\mu}\,\mathrm{d}t}_{\text{value of full repayment}} \\ \underbrace{+\mathbf{1}_{\tau \le T_\mu}\left(\max\{r\bar{p}_\tau - B_\tau, 0\} - f\right)}_{\text{value of defaulting at } \tau} \end{array} \right) \right]$$

Where T_μ exponential$(r\mu)$ is the maturity date of the loan, h_t is utility flow of the house at time t, b is the amount of repayment at each time, $\bar{p_\tau}$ is the liquidation price of the house, f is fixed default cost, the borrower believes that date of the next natural disaster T has exponential distribution with parameter $r\lambda$, $\tau \wedge T_\mu$ is min (τ, T_μ) and (normalized) remaining balance B_t is defined as:

$$B_t \equiv \int_t^{T_\mu} re^{-r(s-t)} b ds$$

Unlike Bakkensen et al., 2023 that h_t is fixed h before the natural disaster and $h - d$ after the natural disaster shock, we use a more comprehensive functional form that not only is related to natural disaster timing but also to the timing public hazard disclosure such as the house getting located in fire hazard zone maps.

The lender, maximizes their profit given the optimal default cost function of the borrower and the loan costs given their belief on timing of the natural disasters and public hazard disclosure. Then, the optimal contract $\mathbf{m} = (l, b, \mu)$ can be obtained by solving the search and matching model with endogenous search friction as the following:

$$U_\lambda \equiv \max_{\alpha_m, \mathbf{m}} \alpha_m \cdot \underbrace{[-r(p-l) + V_\lambda(\mathbf{m})]}_{\text{PV of buying a house with leverage}} + (1-\alpha_m) \cdot \underbrace{(v_\lambda - rp)}_{\text{PV of buying without leverage}},$$

s.t.

$$\eta(\alpha_\mathbf{m})\Pi_{\tilde{\lambda}}(\mathbf{m}) = \kappa_0 \text{ (Free Entry)}$$

Cash Flow Constraint

Where α_m is the endogenous probability that the borrower finds the lender, $\eta(\alpha_m)$ is the probability that the lender finds the borrower (η is an exogenous mapping), p is the price of the house, l is the loan amount, and v_λ is the aggregate value that the buyer receives from the house from time 0 to infinity.

$$v_\lambda \equiv \mathbb{E}_\lambda \int_0^\infty r e^{-rt} h_t \, \mathrm{d}t = h - \frac{\lambda}{1+\lambda} d$$

This setup enables us to find:
1. Optimal default timing of the borrower that depends not only on the timing of natural disaster (similar to Bakkensen et al., 2023), but also on the timing of public disclosure of hazards.
2. Find the optimal contract where the cash flow that is related to the prior belief is also binding.
Further extensions of can be that the households are modeled with Bayesian learning. Insurance-related mechanisms can also be additional extensions of the model. Finally, the comparative statics of the solution of the above model will be used as a supporting backbone of the empirical evidence by the empirical specification described in the next part.

3 Empirical Strategy

To empirically test the theoretical claims, we first take advantage of a historical policy change carried out by the the California Department of Forestry and Fire Protection (CAL FIRE), which updated its Fire Hazard Severity Zones (FHSZ) in 2007. We begin with a simplified natural experiment event-study specification using staggered Difference-in-Difference (DiD):

$$\begin{aligned}\log(Y_{it}) = &\sum_{\tau \neq -1} \left[\beta_\tau^{Mod} D_{it}^\tau \cdot \text{Moderate}_i + \beta_\tau^{High} D_{it}^\tau \cdot \text{High}_i + \beta_\tau^{Vhigh} D_{it}^\tau \cdot \text{VeryHigh}_i\right] \\ &+ \mathbf{X}_{ct}\kappa + \alpha_i + \gamma_{ct} + \varepsilon_{it}\end{aligned}$$

Y_{it} is the outcome variable (e.g., price, whether it is leveraged, and maturity duration of the contracts) of house i on month t. D_{it}^τ indicates whether house i is in the treated group at

time t, that is, it was newly designated in the FHSZ zones. We interact this dummy variable with different fire hazard severity levels (moderate, high, and very high). $\mathbf{X}_{ct}$ is a set of time-varying county-level controls, such as local unemployment, school quality, and average income. α_i is household fixed effect to control for time-invarying idiosyncratic characteristics of houses. λ_{ct} is county-time fixed effect - controlling for aggregate trends at each county. The standard error is robust and clustered at the county level. The coefficients of interest are the set of β_τ showing the average treatment on the treated (ATT) at τ weeks or months relative to the treatment time at different hazard severity level. In order to prevent biases from heterogeneous treatment timing, we employ the method of Callaway and Sant'Anna, 2021. This method non-parametrically estimates group-time average treatment effects $ATT(g,\tau)$, making use of not-yet-treated units as controls and permitting dynamic and heterogeneous treatment effects.

Also, similar to Bakkensen et al., 2023 we leverage longer span panel data with the previous FHSZ maps from 2007, to estimate the effects of prior belief on leveraging risky assets:

$$\log(Y_{it}) = \beta FHSZ_i + \delta PessBuyer_c + \gamma FHSZ_i \times PessBuyer_c + \rho \ln Price_{it} + \mathbf{X}_{ct}\kappa + \alpha_i + \gamma_{ct} + \varepsilon_{it}$$

Y is the contract outcome of the house (whether it is leveraged, and maturity duration). FHSZ indicates whether the house is located in the fire hazard zones, and PessBuyer shows whether the county is overall more pessimistic or optimistic about climate change (Yale climate opinion survey is one option for this to leverage). The reset is the same as the previous specification.

4 Context

California's Fire Hazard Severity Zone (FHSZ) maps were created by the California Department of Forestry and Fire Protection (CAL FIRE) in order to classify areas that have wildfire risks. Starting in the mid-1900s, maps of local responsibility areas (LRAs) and state responsibility areas (SRAs) were created. These maps emerged as a crucial resource for categorizing lands into moderate, high, or very high fire hazard levels, taking into account various factors including vegetation, slope, and historical fire behavior.

In 2007, the state officially embraced these maps delineating State Responsibility Areas (SRA), encompassing approximately 31 million acres of predominantly privately held lands that contribute to watershed protection and the management of public resources. The adoption of Chapter 7A of the California Building Code played a significant role in the establishment of new fire-resistant construction standards. This included specific requirements for roofs and siding in areas susceptible to wildfires. SRA designates areas where CAL FIRE holds legal responsibility for fire protection, primarily encompassing rural and wildland regions that present considerable fire hazards. In contrast, the LRA encompasses areas governed by

local authorities, including urban regions, agricultural fields, and arid landscapes that do not significantly impact watershed dynamics. Since approximately 2008, CAL FIRE has initiated the release of recommended maps indicating areas of "very high" risk for local responsibility areas (LRA).

The counties were then mandated to adopt these maps or present their own rationale for alternative approaches. In certain instances, local governments resisted the adoption of a product, often driven by fears about potential impacts on real estate values, or opted to rename zones to mitigate adverse effects on the market. The policy reforms implemented following 2007 significantly improved the impact of the FHSZ maps. Senate Bill 1241, enacted in 2012, required local governments to integrate wildfire hazard planning into their general plans, utilizing the official Fire Hazard Severity Zone data. This connected land use planning, building permits, and real estate transactions more closely to hazard maps. As time passed, the maps became more than just a scientific resource for assessing wildfire risk; they also evolved into a legal and planning framework that influences development, construction practices, and insurance policies in California. This change in policy demonstrates the interaction between mapping and regulation in addressing wildfire risk within both state- and locally managed regions.

5 Data

5.1 Data Sources

For the housing market, we use the Cotality data set[1]. We obtain the transactional sale amount of the houses, historical characteristics of the houses, and information on the mortgage contracts for each transacted house. Additionally, we use the public Fire Hazard Severity Zones maps provided by the California Fire Department. By having the longitude and latitude of the houses in the Cotality data and implementing Geographic Information System (GIS) methods, we flag the houses in the severity zones. Finally, we use the county-level Yale Climate Opinion Survey (Howe et al., 2015) for belief in climate change measures.

5.2 Data Summary

The time frame of our study is between the years 2000 and 2016. Figure 1 shows the histogram of the observations in this time period. Table 1 provides the summary of several covariates related to house characteristics in different FHSZ classes (i.e., LRA: Very High, SRA: Very High, SRA: High, SRA: Moderate, and the rest of the sample indicated as "control"). Figure 2 displays the geographical distribution of the FHSZ maps throughout California. Figure 3 illustrates the number of unique house IDs in each county by different FHSZ classes. As suggested in the Figure 2 and Figure 3, the majority of the houses included in the FHSZ maps are located in southern part of California. Figure 4 shows the changes in

[1]This dataset was previously knows as CoreLogic.

house prices in different FHSZ classes. Figure 5 shows the share of mortgaged purchases over time.

6 Empirical Results

Note: This section is still a work in progress as we are still waiting to hear from the officials of the CAL FIRE to provide us with the starting date of the publication and adoption of the FHSZ maps in each county. Assuming that all counties adopted the FHSZ maps in 2007 (which is not a valid assumption), and using a basic Difference in Difference model, the baseline estimates of the effects of the LRA and SRA maps on housing prices are presented in Table 2 and Table 3. We do not observe significant effects of being exposed to areas of severity of LRA. However, the effects are statistically significant for the houses located in "very high" risk areas in SRA maps.

Figures

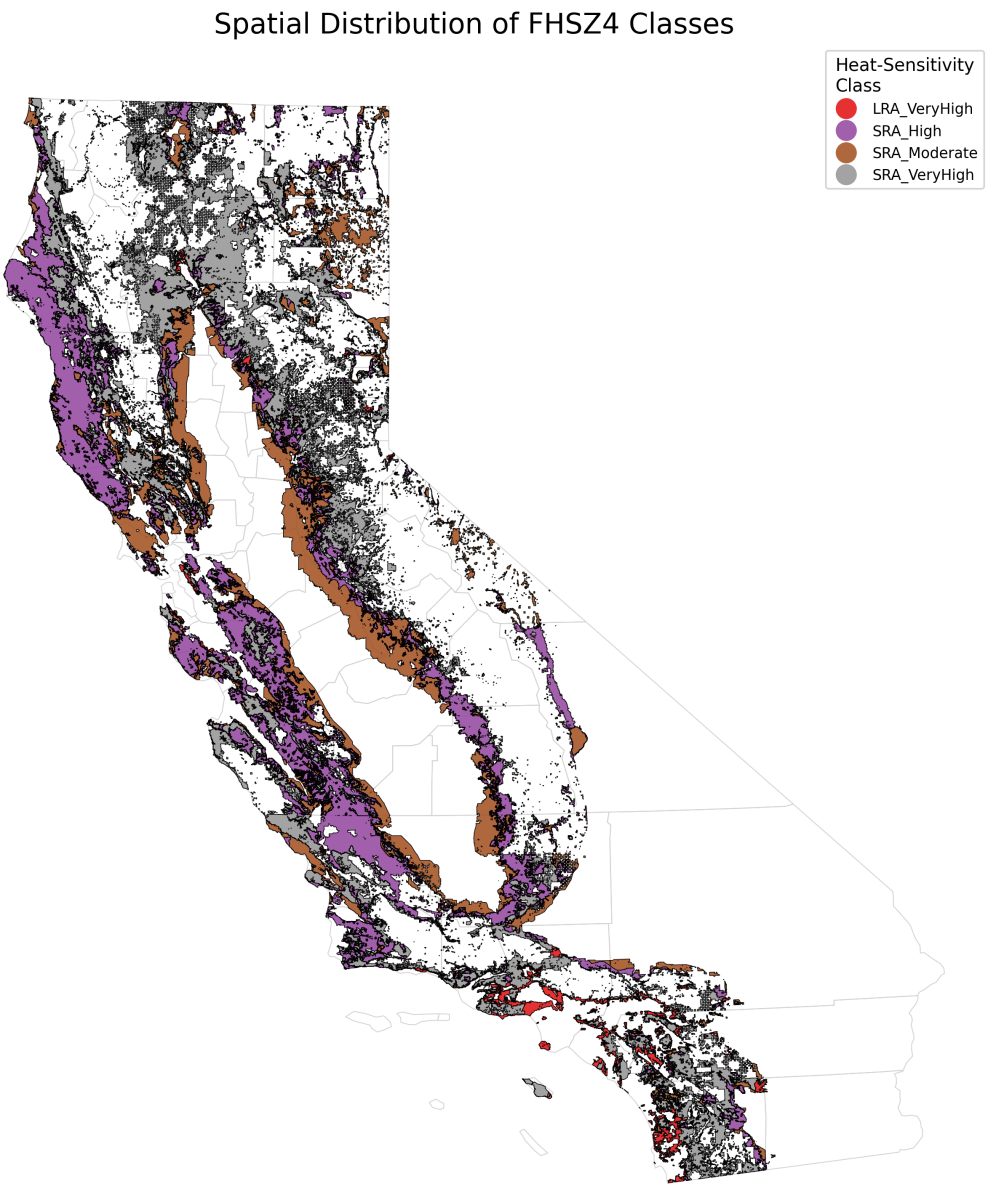


Figure 2: Spatial Distribution of FHSZ classes

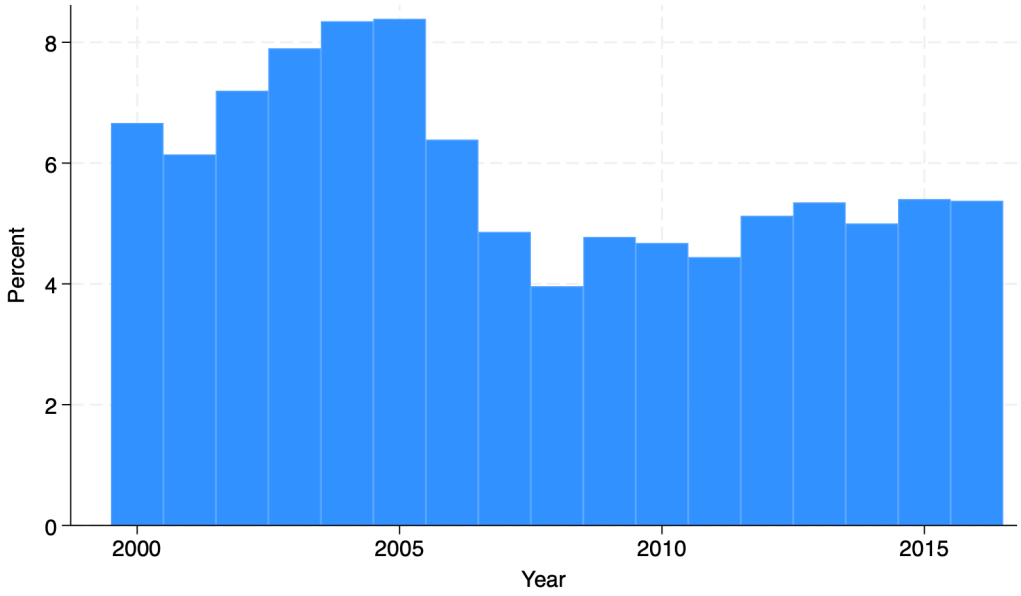


Figure 1: Transaction Year

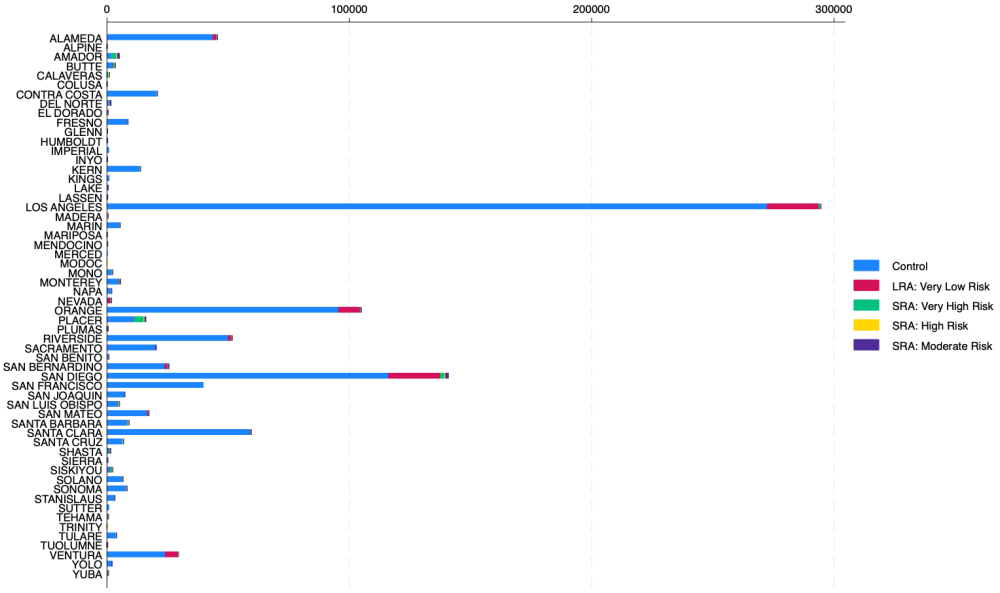


Figure 3: Number of unique clips in each county

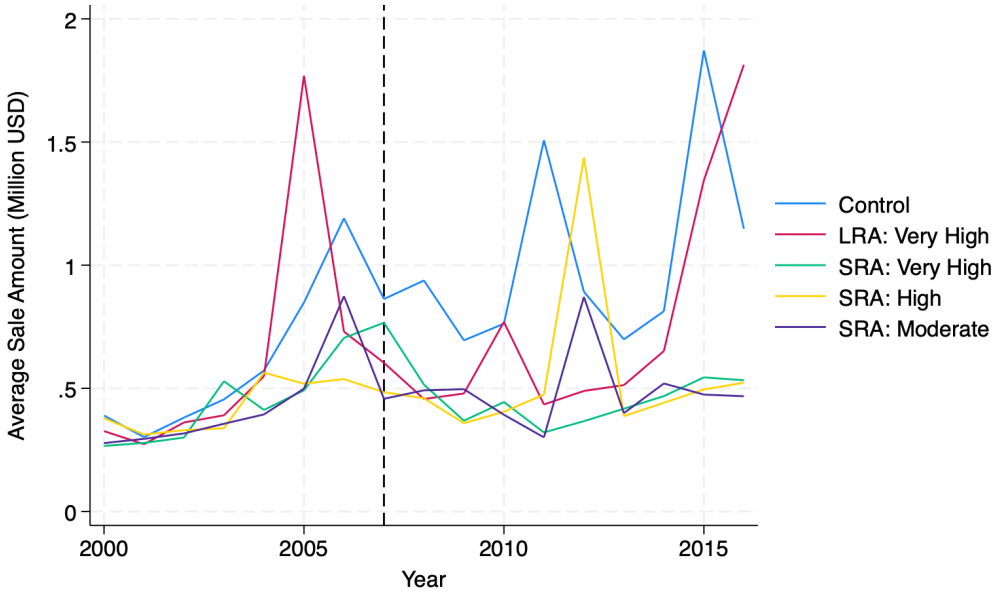


Figure 4: Transactional sale amount in different FHSZ classes

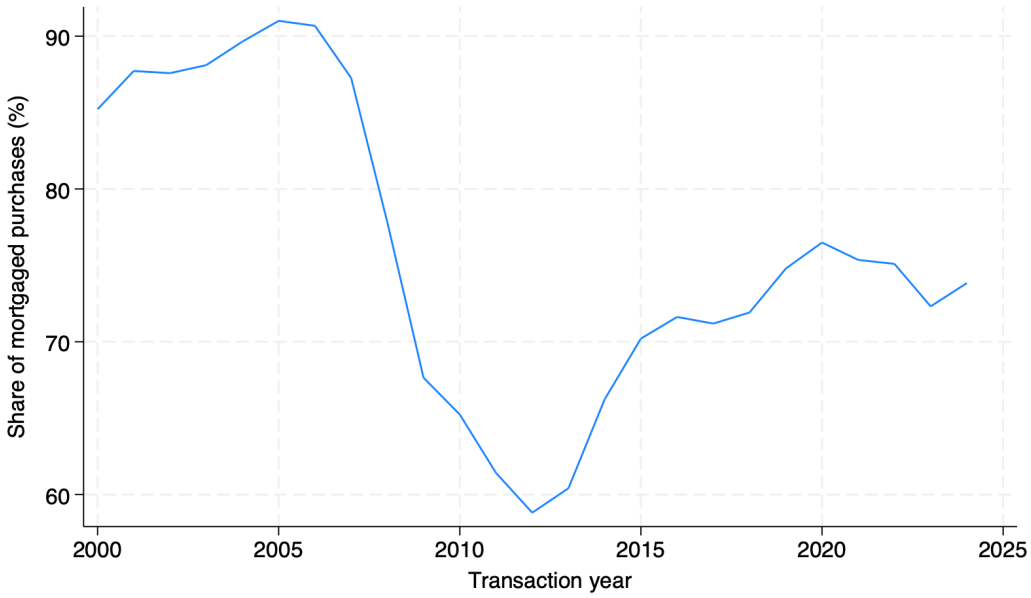


Figure 5: Share of Mortgaged purchases over time

Tables

	(1) Control mean/sd	(2) LRA: Very High mean/sd	(3) SRA: Very High mean/sd	(4) SRA: High mean/sd	(5) SRA: Moderate mean/sd
TOTAL AREA SQUARE FOOTAGE - ALL BUILDINGS	3471.35	1620.15	1561.37	2176.89	1740.70
	(619165.16)	(4138.60)	(1275.35)	(7311.34)	(1144.19)
TOTAL LIVING AREA SQUARE FEET - ALL BUILDINGS	2426.24	1548.50	1503.15	1982.41	1712.91
	(221817.43)	(3420.89)	(1145.35)	(5880.43)	(1005.60)
BUILDING AREA SQUARE FEET	3423.40	1579.40	1546.84	1920.71	1726.69
	(621908.09)	(3424.66)	(1260.04)	(2046.92)	(1130.63)
TOTAL NUMBER OF UNITS - ALL BUILDINGS	21.60	9.88	16.31	2.92	5.09
	(66.13)	(37.11)	(60.83)	(10.52)	(15.58)
UNIVERSAL BUILDING SQUARE FEET	2344.40	1501.79	1484.49	1811.36	1703.03
	(221814.09)	(2857.33)	(1125.97)	(1673.00)	(996.13)
TOTAL NUMBER OF STORIES	1.65	1.69	1.57	1.51	1.55
	(3.29)	(0.81)	(0.69)	(0.75)	(0.74)
TOTAL NUMBER OF BATHROOMS	2.49	2.29	2.08	2.36	2.42
	(4.37)	(2.10)	(1.10)	(0.75)	(0.70)
TOTAL NUMBER OF BATHROOMS - ALL BUILDINGS	2.64	2.45	2.14	2.58	2.49
	(4.73)	(2.87)	(1.03)	(4.44)	(0.92)
TOTAL NUMBER OF ROOMS - ALL BUILDINGS	5.48	5.26	6.08	7.57	5.91
	(6.90)	(1.74)	(2.22)	(15.70)	(2.62)
TOTAL NUMBER OF BEDROOMS - ALL BUILDINGS	2.92	2.58	2.44	3.01	2.74
	(4.81)	(3.14)	(1.25)	(4.61)	(1.14)
YEAR BUILT	1976.53	1982.02	1976.10	1977.01	1976.62
	(24.46)	(19.74)	(25.48)	(33.37)	(26.84)
EFFECTIVE YEAR BUILT	1981.74	1985.55	1977.18	1981.96	1989.77
	(19.57)	(16.28)	(27.63)	(32.53)	(51.67)
TOTAL LAND SQUARE FOOTAGE	79139.73	98004.78	341527.96	208655.72	281420.61
	(1.92e+06)	(350378.82)	(6.19e+06)	(602156.98)	(4.90e+06)
TOTAL NUMBER OF ACRES	1.81	2.23	7.84	4.79	26.00
	(43.98)	(7.16)	(142.02)	(13.82)	(1231.48)
NUMBER OF BUILDINGS	1.05	1.02	1.02	1.05	1.02
	(0.31)	(0.18)	(0.18)	(0.25)	(0.17)
Observations	1440671	107585	21163	6346	9143

Table 1: Summary of the Houses Characteristics in Different FHSZ classes

	(1)	(2)	(3)
LRA	0.0753	0.107*	0.108***
	(0.0542)	(0.0534)	(0.0331)
Post	0.0978*	0.0148	1.024***
	(0.0569)	(0.0594)	(0.0331)
LRA × Post	-0.00179	0.0155	0.0107
	(0.0430)	(0.0461)	(0.0459)
Total Area (Square feet)		7.37e-09	6.58e-09
		(7.25e-09)	(6.93e-09)
N. of bedrooms		0.0427***	0.0431***
		(0.00790)	(0.00651)
Year Fixed Effects	N	Y	Y
County Fixed Effects	N	N	Y
R^2	0.00341	0.0581	0.269
N	1705998	1377154	1377154

Standard errors in parentheses

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

Table 2: Difference in Difference Preliminary Estimates for the Effects of LRA Maps

Note: The left-hand-side independent variable is log(sale price). LRA dummy is equal to one if the house is located in a "very high" risk in LRA maps and zero otherwise. "Post" dummy is equal to one for years after 2007 and zero for years before. The houses located in risky areas of SRA maps are excluded. Robust Standard Errors are clustered at county level.

	(1)	(2)	(3)
Moderate	0.0345	0.0987	0.155***
	(0.123)	(0.118)	(0.0528)
High	-0.0731	-0.0209	0.209**
	(0.0951)	(0.0885)	(0.0788)
Very high	-0.0821	-0.00946	0.101
	(0.108)	(0.119)	(0.0665)
Post	0.0978*	0.0148	0.993***
	(0.0569)	(0.0593)	(0.0336)
Moderate × Post	-0.239***	-0.103	-0.0293
	(0.0836)	(0.0990)	(0.115)
High × Post	-0.238*	-0.0343	-0.0693
	(0.120)	(0.0942)	(0.101)
Very high × Post	-0.301***	-0.201***	-0.167**
	(0.0987)	(0.0711)	(0.0760)
Total Area (Square feet)		7.14e-09	6.47e-09
		(6.99e-09)	(6.71e-09)
N. of bedrooms		0.0425***	0.0429***
		(0.00809)	(0.00665)
Year Fixed Effects	N	Y	Y
County Fixed Effects	N	Y	Y
R^2	0.00436	0.0574	0.273
N	1627688	1304861	1304861

Standard errors in parentheses

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

Table 3: Difference in Difference Preliminary Estimates for the Effects of SRA Maps

Note: The left-hand-side independent variable is log(sale price). "Post" dummy is equal to one for years after 2007 and zero for years before. The omitted category is for the houses that are not located in any of SRA maps. Houses located in very high risk areas of LRA maps are excluded. Robust Standard Errors are clustered at county level.

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Climate Change and Mortality: Evidence from Iran*

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Abstract

Due to the prominence of the evaluation of the consequences of rising temperatures, this paper examines the effects of temperature variation on mortality across different demographic groups in Iran. We use a rich weekly data set from 2009 to 2017 across different demographic groups to understand the potential health impacts of climate change in a developing country. Using several fixed effect regressions, we discover that for an additional day with a mean temperature over 25°C, mortality rate increases by 2.56% relative to the effects of an extra day in 0-5 °C, in the weekly temperature exposure horizon. we test for the harvesting effect by comparing the estimates at weekly and monthly temperature exposure windows. As we widen the temperature exposure window in hot temperatures, the aforementioned estimate shrinks to 0.53%. Broadening the temperature exposure horizon, we demonstrate that the estimates for infants and seniors, in contrast to other demographic groups, remain large and significant.

Keywords: Climate Change, Mortality, Temperature, Health

JEL Codes: Q50, Q54, Q58, I12

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1 Introduction

Due to the accumulation of greenhouse gases, the number of studies evaluating the dire consequences of climate change has expanded in the past few years. As the weather extremes are becoming more frequent and more people are exposed to their damages, it is crucial to understand how climate change affects human life and how people can adapt to them.

Evidence has been accumulating on the aspects on which rising temperatures have an impact. Income, productivity, consumption, human capital, agricultural production, conflict, health, and mortality are some of these aspects (e.g., Burke et al., 2015; Schlenker and Roberts, 2009; Deschênes and Greenstone, 2007; Burke et al., 2009; Hsiang et al., 2013; Jacob et al., 2007; Skoufias and Vinha, 2013; Baez et al., 2010). Mortality is among the most prominent aspects since it reflects the very existential part of all individuals' lives.

Not only is it crucial to evaluate the effects of rising temperatures on mortality, but also researchers have to distinguish such effects in developed and developing countries. While several pieces of research have estimated the potential health damages of the rising temperature in developed countries (e.g., Deschênes and Greenstone, 2011; Barreca et al., 2016; Heutel et al., 2021), there are few papers assessing the adverse effects of climate change in developing countries, which are assumed to be more fragile confronting weather shocks (Sen, 1981, Townsend, 1994). In one of few exceptions, Burgess et al., 2017 find that hot days cause a considerable increase in mortality in rural India but not urban India. Using comprehensive province-level mortality data from Iran from 2009 to 2017, this paper provides additional support for the argument that people in developing countries are more vulnerable to rising temperatures.

Warmer weather can negatively affect human health through several mechanisms. Burgess et al., 2017 categorizes these mechanisms into two major groups, direct and indirect effects. Both high and low temperatures increase the heart rate to raise blood flow from the body to the skin. Therefore, weather variation can significantly cause cardiovascular diseases, triggering specific health problems. A warmer climate can create a suitable environment for the

proliferation of pathogens. Moreover, indirect effects occur through income reduction; the higher the temperatures, the lower the productivity and income. Households whose income has decreased due to the rising temperatures may spend less on health and proper nutrition. Several pieces of research evaluate the effects of rising temperatures on human health and examine the application of complex structural and empirical models by including short-run and long-run adaptation. For example, during 1992-2013, both hot and cold days heightened mortality in the United States of America. However, hot days are more deadly in cool areas, while cold days are more deadly in hot regions of the US (Heutel et al., 2021). Likewise, hotter areas are better shielded against the mortality impacts of high temperatures in the US subperiods of the twentieth century (Barreca et al., 2015). Most of these papers are in the context of developed countries, and less is known about the adaptation in developing countries. In one of the few exceptions, Burgess et al., 2017 show that the negative effects of high temperatures alleviate by the expansion of bank branches in rural India.

While the majority of the studies use average temperature as the main independent variable, few studies implement maximum and minimum temperatures in their analysis. Furthermore, some studies control for other weather variables such as relative humidity (e.g., Barreca, 2012), dew temperature, and heat index. However, these additional controls do not change the estimates meaningfully (Deschenes, 2014).

Most of the economic studies find that extreme temperatures cause a significant increase in mortality. They suggest a day with average temperature less than 40 °F or higher than 90 °F, causes the annual mortality rate to increase by 0.1% in the US. Barreca et al., 2016 report the same results. The cause of death in heat-(cold) related mortality is also worth noticing. The primary cases of death impacted by the extreme temperatures are cardiovascular and respiratory diseases (Deschenes, 2014).

The impacts of rising temperatures are heterogeneous across different age groups and gender. Deschênes and Greenstone, 2011 find that these effects do not change in magnitude as the age increases. They also report that these effects are similar in both genders.

Some of the estimates in the mentioned papers are subject to potential estimation bias. For example, there is a potential source of endogeneity because of needing to control air pollution. In developing countries, specifically Iran, as many cities are exposed to severe air pollution, ignoring air quality leads to potential omitted variable bias estimation. Indeed, air quality and temperature are correlated; the lower the temperature, the more airborne particles' density is due to the air inversion effect. Additionally, increasing CO in the prior two weeks causes a significant increase in mortality rates in six metropolitan areas of Tehran, Ahvaz, Mashhad, Tabriz, Shiraz, and Esfahan during 2011-2015 in Iran (Rahmati, Moghani, and Vesal, 2020).

Deschenes and Moretti, 2009 emphasize the importance of mortality harvesting in weather-related mortality. This effect involves changing the timing of death by a few days or weeks. In other words, if a high-temperature shock does not occur, those individuals whose health is already compromised would die a few days later. Deschenes and Moretti, 2009 indicate that near-term displacement, or harvesting effect, explains almost all mortality spikes aroused from high temperatures.

Finally, it is crucial to check whether the estimates are robust. Most of the studies allow for a dynamic relationship between temperature and mortality. Studies based on daily data tend to include distributed lags in temperature and to compute cumulative effects (e.g., Curriero et al., 2002, Deschenes and Moretti, 2009). On the other hand, Studies based on longer time horizons (e.g., monthly or annual) focus on time-aggregating the daily temperature data in a manner that allows for sufficient post temperature shock mean-reversion thereby alleviating bias estimation caused by mortality harvesting effect (e.g., Barreca et al., 2016, Deschênes and Greenstone, 2011).

I employ fixed effect regressions in order to estimate the effects of temperature variation on mortality. We use a rich weekly data set from 2009 to 2017 across 21 age groups for each gender. Our high-frequency data set lets us compare weekly and monthly temperature

exposure window results. We discover that hot days cause a considerable rise in mortality in the weekly temperature exposure window. For example, an additional day with a mean temperature more than 25 °C increases the mortality by 2.56%, relative to the effects of an additional day in 0-5 °C. We test for harvesting effect by comparing the estimates at weekly and monthly temperature exposure windows. As we enlarge the temperature exposure horizon from a week to a month, this estimate drops to 0.53% but remains statistically significant. In contrast to the weekly temperature exposure window, our results for middle-aged individuals and seniors are negligible and insignificant when we use a monthly temperature exposure window. The harvesting effect can explain this finding since older people are more susceptible to climate variation.

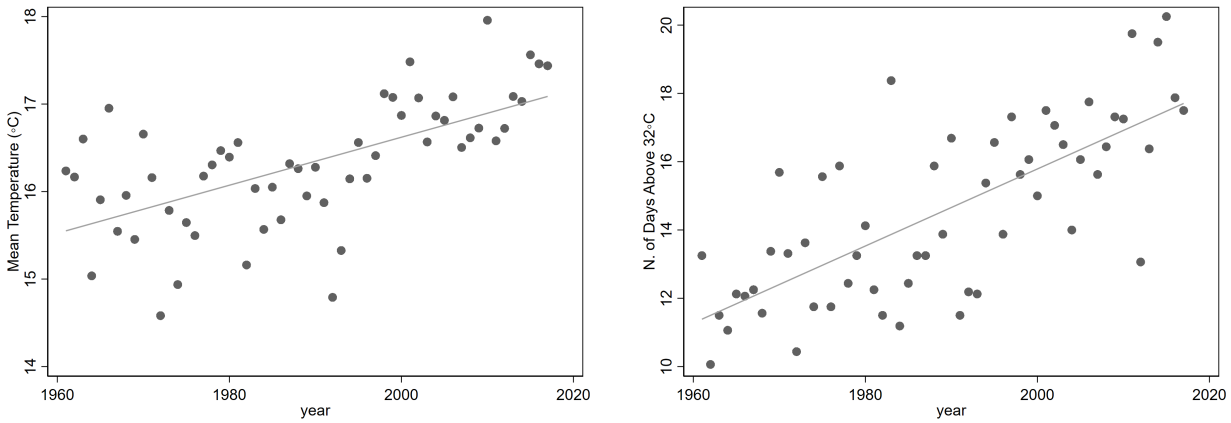
In the next section, we briefly provide background on climate change in Iran and the data implemented by our analysis in section 2. We demonstrate our empirical methods in section 3. Section 4 describes our results, and section 5 concludes.

2 Context and Data

In this section, we first briefly outline the evidence of climate change and mortality in Iran. After that, we explain the the sources of our data set. Finally, we describe the data.

2.1 Context

Current scenarios of climate change predict warmer temperatures, comparatively different rainfall patterns across the globe, and more frequent and intense extreme weather events ([IPCC, 2018] and [Auffhammer, 2018]). Iran has several unique characteristics that makes studying it interesting. Therefore, discussing the severity and intensity of climate change in Iran is necessary. Iran is located in Western Asia with several indistinct area coverage types of climates, namely 35.5% hyper-arid, 29.2% arid, 20.1% semi-arid, 5% Mediterranean, and 10% wet (of the cold mountain type) ([Amiri et al., 2010]). In the past 60 years, the



(a) Annual mean temperature

(b) Number of days above 32 °C

Figure 1: Temperature Trend in Iran

Notes: Panels A and B show the average annual temperature and number of days with an average temperature above 32 ∘C in Iran from 1961 to 2018, respectively. Here we only use the data from 16 weather monitoring stations established before 1961 and do not have any missing daily reports from 1961-2018. Figure A.5 illustrates aforementioned stations.

average temperature has increased somewhat by more than one degree of Celsius, slightly higher than the global average (Figure 1a). Sweltering days above 32 ∘C are also becoming more frequent (Figure 1b). However, the temperature rise distribution among provinces is distinctive (Figure 2). Northwest regions, which are relatively colder provinces (Figure A.3), experience more temperature rises (Figure 2).

The average annual rainfall in Iran is around 250 mm, but it varies from less than 100 mm in the east to more than 2000 mm in the north, resulting in various climates in Iran. By and large, Iran is classified as dry and semi-arid, with low rainfall and high evapotranspiration (Khalili et al., 2016). Ghaedi and Shojaian, 2020 investigate precipitation trends in Iran and show no significant trend in most weather stations (107 out of 113 stations) during 1988-2017. Likewise, our data is consistent with the previous claim (Figure 3a). However, the number of days with precipitation has decreased, resulting in more frequent and intense floods (Figure 3b). Moreover, humidity has diminished in this period (Figure A.1).

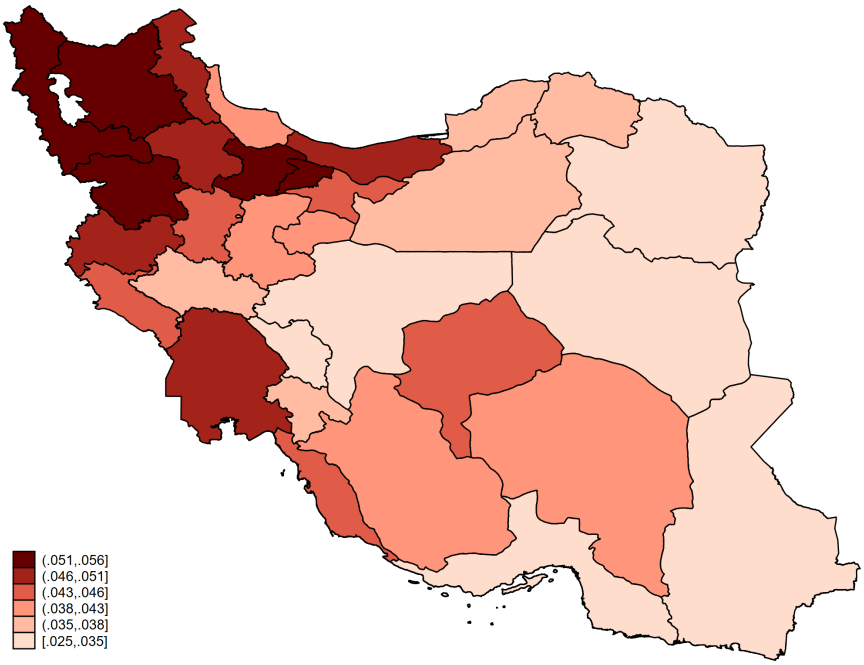


Figure 2: Average annual temperature rises in Iran by provinces

Notes: Figure shows province-level yearly average temperature rises [in Celsius degrees] in Iran, from 1966 to 2017.

2.2 Data

Weather data. — The weather data are provided by Iran Meteorological Organization (IMO). The weather data contains daily records of 411 weather monitoring stations from 1960 to 2018. As the mortality data is available after 2009, we restrict our data to our analysis period from 2009 to 2017. Consequently, we narrow our observation to the reports of the stations established before 2009. To avoid missing values, we eliminate the data obtained by the stations that have failed to report on all days during this period. Therefore, our analysis is based on the reports of 237 stations. This strict station qualification protects our study from data distortions. However, this restriction excludes Qom province, as no weather monitoring station fulfills our criteria. The location of these stations is presented in Figure A.6. We also used 16 monitoring stations to illustrate long-run trend in climate during 1961-2018. These stations have no missing value in that period, and Figure A.5 demonstrates their location. Our final data set does not suffer from any plausible distortions

or existing missing values.

Mortality data. — The mortality data are provided by National Organization for Civil Registration (NOCR). In our analysis period, 2009-2017, almost 3 million deaths have been recorded. This province-level data is constructed weekly, enabling us to capture abrupt weather mortality. Altogether, our mortality data reports weekly death counts by gender and 21 age categories, as illustrated in Figure A.2. In order to obtain the rate of mortality in each demographic group we use the population data from the Iran's population census provided by Statistical center of Iran in 2016.

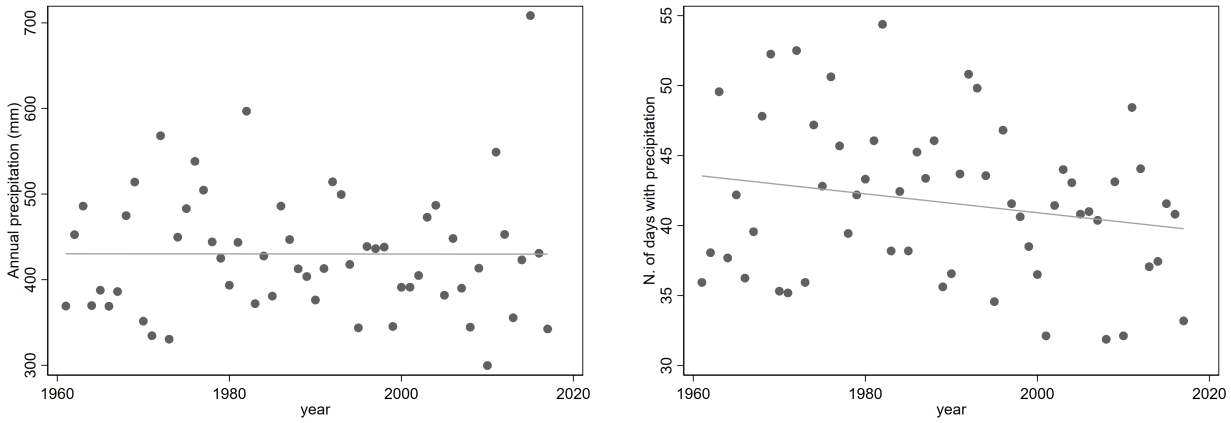
2.3 Data Description

Table 2 demonstrates the mean and standard deviation of mortality by the province in each demographic group. Also, Table 1 provides a summary of monthly mortality rate. We let the weather mortality vary by ten temperature bins, which are "below -5 °C", "-5-0 °C", "0-5 °C", "5-10 °C", "10-15 °C", "15-20 °C", "20-25 °C", "25-30 °C", "30-35 °C", and "above 35 °C". Figure 4 shows the distribution of daily mean temperature. Moreover, Figure A.2 illustrates the distribution of deaths across demographic groups. It is worth mentioning that for all age categories, except for adults, the average number of provincial weekly recorded deaths in the "cold" seasons (i.e., autumn and winter) are significantly higher than in the "hot" seasons (i.e., spring and summer). This difference is considerably higher in senior people (i.e., people with age more than 60) (Table 3).

Table 1: Average Monthly Mortality Rate, by Province

	Gender		
	Female	Male	Total
Age Groups			
Infant			
Mean	0.934	0.716	0.825
Standard deviation	1.054	0.434	0.813
Child & Teen			
Mean	0.097	0.076	0.086
Standard deviation	0.206	0.060	0.152
Adult			
Mean	0.072	0.139	0.105
Standard deviation	0.085	0.054	0.079
Middle Age			
Mean	0.174	0.318	0.246
Standard deviation	0.097	0.081	0.114
Senior			
Mean	2.292	2.686	2.489
Standard deviation	0.525	0.520	0.558
Total			
Mean	0.714	0.787	0.750
Standard deviation	1.007	1.023	1.015

Notes: "Infant," "Child & Teen," "Adult," "Middle Age," and "Senior" represent the number of people dying at ages 0, 1-19, 20-39, 40-59, and 60+, respectively. Monthly mortality rate is the total number of deaths divided by their population in 2016 times 1000.



(a) Annual precipitation (mm)

(b) N. of days with precipitation

Figure 3: Precipitation trend in Iran

Notes: Panel A and B show annual precipitation [in millimeters] and the number of days with precipitation higher than 1mm in Iran from 196 to 2018, respectively. Here we only use the data from 16 weather monitoring stations established before 1961 and do not have any missing daily reports from 1961-2018. Figure A.5 illustrates the aforementioned stations.

Table 2: Average Mortality in a Week, by Province

	Gender	
	Female	Male
Age Groups		
Infant		
Mean	4.454	3.964
Standard deviation	5.466	4.735
Child & Teen		
Mean	7.342	6.914
Standard deviation	12.985	7.606
Adult		
Mean	7.959	15.924
Standard deviation	10.930	13.974
Middle Age		
Mean	12.246	22.719
Standard deviation	16.069	23.255
Senior		
Mean	68.525	77.375
Standard deviation	68.884	74.668

Notes: "Infant," "Child & Teen," "Adult," "Middle Age," and "Senior" represent the number of people dying at ages 0, 1-19, 20-39, 40-59, and 60+, respectively.

Table 3: Average Mortality in a Week in Cold and Hot Seasons, by Province

	Cold	Hot	Diff	tstatistics	pvalue
Infant	2338.15	2163.08	175.07	57.83	0.00
Child & Teen	3948.84	3629.92	318.92	126.68	0.00
Adult	6413.59	6465.96	-52.37	-14.94	0.00
Middle Age	9897.84	9259.12	638.72	128.76	0.00
Senior	42599.80	37921.72	4678.08	271.41	0.00

Notes: Columns 1 and 2 in the table illustrate the average provincial deaths across age categories and seasons, and in the following columns, we compare. "Infant," "Child & Teen," "Adult," "Middle Age," and "Senior" represent people dying at ages 0, 1-19, 20-39, 40-59, and 60+, respectively. The cold season is defined as autumn and winter. The hot season is defined as spring and summer.

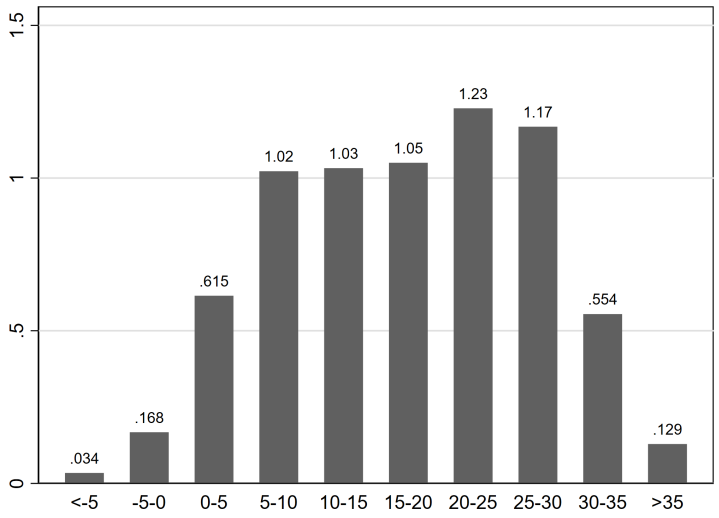


Figure 4: Distribution of daily mean temperatures in a week

Notes: The figure shows the distribution of daily average temperature across ten temperature bins between 2009 and 2018. More indicatively, each bar represents the average number of days per week in each temperature bin. The leftmost bin measures number of days with a mean temperature less than -5 °C and the rightmost bin is the number of days where the mean temperature exceeds 35°C. The inverting eight bins are all 5°C wide. The numbers above the bars correspond to height of each bar.

3 Empirical Methodology

In this section, we explain our econometric models employed to estimate the impact of temperature variation on mortality rate. Firstly, we estimate the following equation, a fixed effect regression using province and time fixed effects, for the province-level mortality rates of various demographic groups.

$$\log(M_{pydw}) = \sum_{j} \theta_j TEMP_{j_{pyw}} + \sum_{l} \rho_l PRECEP_{l_{pyw}} + \alpha_{pd} + \lambda_{ym} + \varepsilon_{pywd} \tag{1}$$

The dependent variable, M_{pywd}, is the mortality rate for demographic group d, in the year y and the week w, and province p. We use 10 separate demographic groups defined by the interaction of 5 age categories (0, 1-19, 20-39, 40-59, and 60+) and gender (male and female). $TEMP$ is the set of temperature variables indicating the number of days province p is exposed to mean temperature in a given temperature bin j (e.g., 25-30 °C). Our set of temperature bins consists of ten temperate bins, of which inverting eight bins are all 5°C wide[1]. $PRECEP$ is our weekly precipitation control set, which includes four categories[2]. Also, equation (1) includes a comprehensive set of province-by-demography fixed effects, α_{pd}, which absorb all unobserved province-specific time-invariant heterogeneity of the mortality rate for each demographic group. As an illustration, the overall health characteristics of each province's inhabitants will not lead to omitted variable bias estimation. The equation (1), also consists of month-year indicators, λ_{ym}. This enables us to control for time-varying differences in the mortality rate in Iran, such as seasonal deaths, as depicted in Table 3. The variable of primary interest in the equation (1) is $TEMP_j$, and the coefficient θ_d captures the impact of being exposed, for an additional day, to a particular temperature bin compared to the reference bin (i.e., 0-5 °C).

Since weather fluctuations are somehow orthogonal to mortality's unobserved variables, our

[1] The set of temperature bins is: "<-5 °C," "-5-0 °C," "0-5 °C," "5-10 °C," "10-15 °C," "15-20 °C," "20-25 °C," "25-30 °C," "30-35 °C," and ">35 °C"

[2] 1. zero weekly precipitation, 2. below 1 mm weekly precipitation, 3. 1-30 mm weekly precipitation, and 4. above 30 mm weekly precipitation

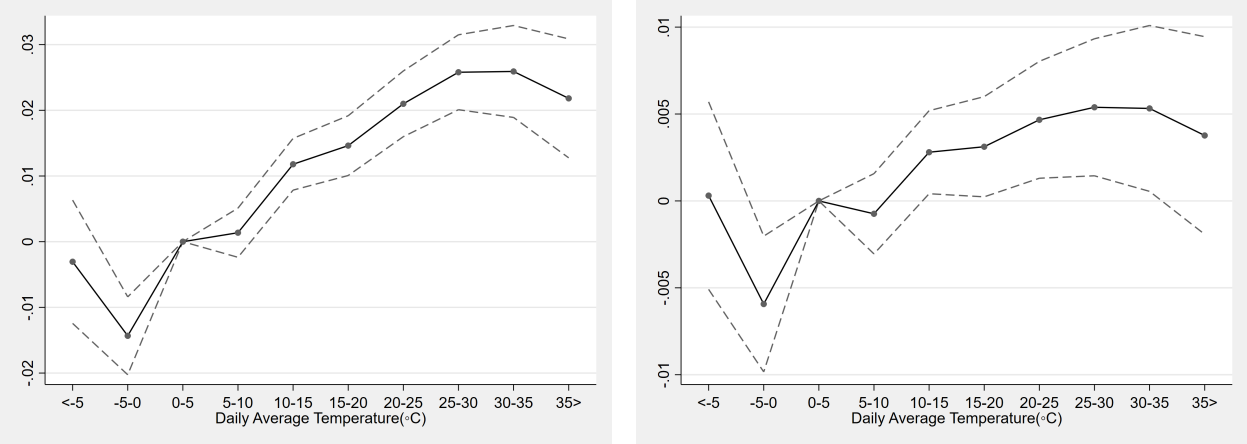
estimation suffers less from endogeneity to an acceptable extent. However, there are still some concerns. First, in equation (1), the time period is weekly, and it may take more than a week for deaths from extreme weather to occur. Secondly, mortality harvesting can be a potential threat in our analysis. Mortality harvesting, or morality displacement, consists of the change of mortality by a few days or weeks, but not the overall mortality in the long run (Deschenes and Moretti, 2009). Had it not been an extreme weather event, some people would have died a few days later. In simple terms, extreme weather events can hasten mortality and may not be the cause of mortality. Therefore, we use equation (2), similar to equation (1), except that it is monthly instead of weekly. Since the full impact of especially hot and cold days is evident within nearly 30 days (Deschenes and Moretti, 2009), our second approach does not suffer from the mortality displacement issue. Also, our second approach can almost alleviate the former concern.

$$\log(M_{pydm}) = \sum_{j} \theta_j TEMP_{j_{pym}} + \sum_{l} \rho_l PRECEP_{l_{pym}} + \alpha_{pd} + \lambda_{ym} + \varepsilon_{pymd} \tag{2}$$

In our second estimation, depicted in the equation (2), M_{pydm} is the number of deaths in province p, in month and year m and y, and for demographic group d. $TEMP$ indicates the number of days in each bin in the month m in province p. Temperature bins are identical to the previous estimation. $PRECEP$ is the monthly precipitation control set, which includes four categories[3]. Fixed effect controls are identical to the equation (1).

In both equations, we report standard errors that allow for heteroskedasticity using clustering in the province-by-demography because it is likely that the error terms are correlated within the province-by-demography.

[3] 1. zero monthly precipitation, 2. below 10 mm weekly precipitation, 3. 10-100 mm weekly precipitation, and 4. above 300 mm weekly precipitation



(a) Weekly Temperature Exposure Window (b) Monthly Temperature Exposure Window

Figure 5: Estimates of Impact of Daily Temperature on Log Mortality Rate

Notes: The plotted lines report coefficient estimates for each temperature bin. Each marker indicates the impact of a single day in each of the 9 temperature bins, relative to the impact of a day in 0-5 °C reference bin, on log mortality rate. Dashed lines represent the 95% confidence interval of the estimates. Panel a and panel b are driven from the equation (1) and equation (2), respectively. Standard errors are clustered in province-by-demography.

4 Results

This section consists of three subsections. First, we provide our baseline estimation results which indicate the impact of temperature on mortality rate, and compare the weekly and monthly estimation coefficients in equation (1) and equation (2). Second, we drive several robustness checks. Finally, we examine the heterogeneous effects across age categories.

4.1 Baseline Estimates

Figure 5a depicts our coefficients estimates derived from the equation (1), which enables us to observe the temperature impacts on a weekly time frame. Estimated coefficients in Figure 5a show an apparent temperature effect on a weekly time frame. Column 3 in Table 4 reports all of the estimated temperature coefficients from equation (1), which is our preferred estimation. Our weekly estimates suggest that an additional day exposed to mean temperature more than 25 °C increases the mortality by 2-2.5%, relative to the effects of an additional day

in the reference bin (i.e., 0-5 °C). Apart from the first and third temperature bins[4], all of the coefficients are statistically significant at 1% level. Generally, as the temperature increases, the impact on mortality rate intensifies. Table 4 also includes other estimations, reported in columns 1 and 2. Column 1 reports the estimates of a regression similar to the equation (1) except that it has province fixed effects instead of province-by-demography fixed effects. The estimation used in column 2 includes demographic fixed effects in addition to the estimation in column 1. Even though these coefficients suffer from estimation bias due to mortality harvesting effect, they are still important as they capture the very short-run effects of rising temperature on mortality.

our second estimation, equation (2), involves a monthly time frame. Therefore, our coefficients, illustrated in Figure 5b), do not suffer from the mortality harvesting estimation bias (Deschenes and Moretti, 2009). As a result, the estimated coefficients are lower. Still, most of the coefficients are statistically significant at 5% level. For instance, employing equation (2), an additional day in 25-30 °C temperature bin by 0.54%, relative to the effect of an extra day in 0-5 °C (Table 5, column 3). Again, Table 5 includes other estimations. Column 1 reports the estimates of a regression similar to the equation (2) except that it has province fixed effects instead of province-by-demography fixed effects. The estimation in column 2 employs demographic fixed effects in addition to the estimation in column 1. Column 3 reports the estimates of equation (2) and is our preferred estimation.

[4]less than -5 °C and 5-10 °C average daily temperature

Table 4: Estimates of the Impact of Different Average Temperatures on Log Mortality Rate on a Weekly Time Frame

	(1)	(2)	(3)
<-5 °C	-0.00421	-0.00289	-0.00305
	(0.00516)	(0.00475)	(0.00477)
-5-0 °C	-0.0144***	-0.0144***	-0.0143***
	(0.00322)	(0.00302)	(0.00301)
5-10 °C	0.00138	0.00134	0.00137
	(0.00213)	(0.00189)	(0.00190)
10-15 °C	0.0106***	0.0118***	0.0118***
	(0.00211)	(0.00200)	(0.00200)
15-20 °C	0.0140***	0.0147***	0.0146***
	(0.00254)	(0.00231)	(0.00231)
20-25 °C	0.0199***	0.0211***	0.0210***
	(0.00279)	(0.00254)	(0.00254)
25-30 °C	0.0249***	0.0260***	0.0258***
	(0.00319)	(0.00291)	(0.00290)
30-35 °C	0.0254***	0.0261***	0.0259***
	(0.00385)	(0.00354)	(0.00356)
>35 °C	0.0209***	0.0221***	0.0218***
	(0.00486)	(0.00460)	(0.00460)
Precipitaion Control	Y	Y	Y
Province-by-Demographic FE	N	N	Y
Province FE	Y	Y	N
Demographic FE	N	Y	N
Monthly date FE	Y	Y	Y
R^2	0.0199	0.871	0.888

Standard errors in parentheses

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

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Notes: Standard errors clustered by province-by-demography are reported in parentheses. Each column is from a separate regression. The dependent variable is log mortality rate. The duration of the temperature exposure window is one week. Column 1 reports the estimates of a regression similar to the equation (1) except that it has province fixed effects instead of province-by-demography fixed effects. The estimation used in column 2 includes demographic fixed effects in addition to the estimation in column 1. Column 3 reports estimates from equation (1)

Table 5: Estimates of the Impact of Different Average Temperatures on Log Mortality Rate on a Monthly Time Frame

	(1)	(2)	(3)
<-5 °C	0.000331	0.000305	0.000306
	(0.00274)	(0.00274)	(0.00274)
-5-0 °C	-0.00571***	-0.00593***	-0.00593***
	(0.00199)	(0.00198)	(0.00198)
5-10 °C	-0.000647	-0.000753	-0.000739
	(0.00118)	(0.00117)	(0.00117)
10-15 °C	0.00288**	0.00280**	0.00280**
	(0.00122)	(0.00121)	(0.00121)
15-20 °C	0.00322**	0.00311**	0.00312**
	(0.00147)	(0.00146)	(0.00146)
20-25 °C	0.00483***	0.00467***	0.00467***
	(0.00173)	(0.00171)	(0.00171)
25-30 °C	0.00556***	0.00539***	0.00539***
	(0.00202)	(0.00200)	(0.00200)
30-35 °C	0.00554**	0.00533**	0.00532**
	(0.00245)	(0.00242)	(0.00242)
>35 °C	0.00409	0.00377	0.00377
	(0.00292)	(0.00289)	(0.00289)
Precipitaion Control	Y	Y	Y
Province-by-Demographic FE	N	N	Y
Province FE	Y	Y	N
Demographic FE	N	Y	N
Monthly date FE	Y	Y	Y
R^2	0.0240	0.920	0.938

Standard errors in parentheses

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

.

Notes: Standard errors clustered by province-by-demography are reported in parentheses. Each column is from a separate regression. The dependent variable is log mortality rate. The duration of the temperature exposure window is one month. Column 1 reports the estimates of a regression similar to the equation (2) except that it has province fixed effects instead of province-by-demography fixed effects. The estimation used in column 2 includes demographic fixed effects in addition to the estimation in column 1. Column 3 reports estimates from equation (2)

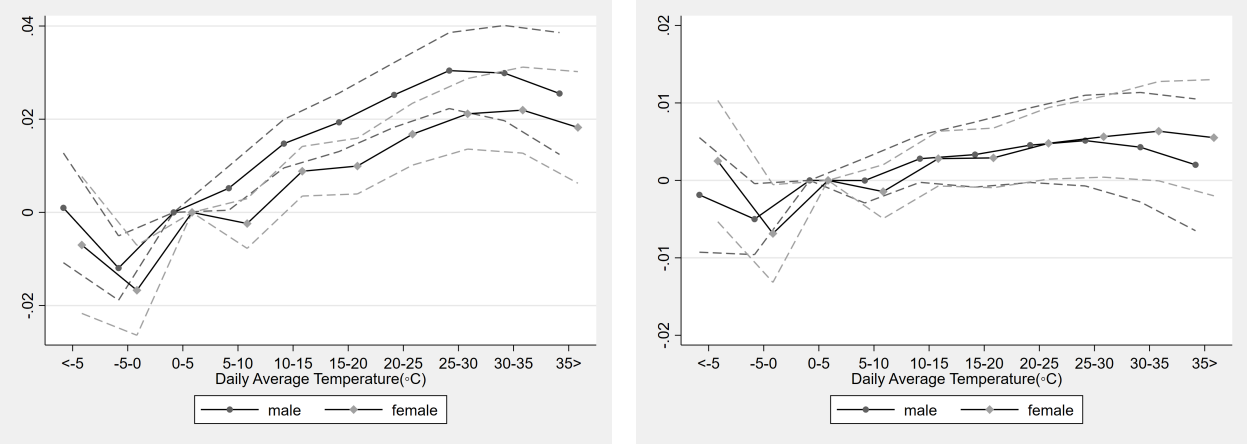
4.2 Robustness and Heterogeneity

The consequences of high temperatures on different age groups are different. Our rich set of morality data among different age groups enables us to observe these impacts independently. We define people who die at ages of "0," "1-19," "20-39," "40-59," and above 60" as "Infant," "Child&Teen," "Adult," "Middle Age," "and Senior." Using a weekly exposure window, equation (1), our analysis suggests that in all of the age categories, people are vulnerable to high temperatures (Table 6).

However, our second approach, with a monthly temperature exposure window, demonstrates that the effects of high temperatures on mortality are idiosyncratic among different age groups. Table 7 reveals the impacts of temperature on mortality rate in different age groups, with a monthly temperature exposure window. These are derived from estimating the coefficients for each demographic group separately. Infants are the most susceptible group, and their estimates are much higher than other age groups. Column 2 in Table 7 suggests that an additional day exposed to mean temperature more than 25 °C increases the mortality rate by about 1.2 %, relative to the effects of an additional day in the reference bin (i.e., 0-5 °C), and these estimates are statistically significant at 5 or 10% level. Adults, Children and teenagers have also relatively large coefficients, even though the coefficients in these groups are not statistically significant at 10% level in high temperatures. Surprisingly, middle age and senior people are almost shielded from high temperatures, and most of the coefficients in the last two columns in Table 7 are neither significant nor large.

our models suggest that most of the impact on middle-aged and senior individuals is due to the harvesting effect. In other words, most middle-aged and senior individuals who die from high temperatures would die in the following few weeks if they were not exposed to high temperatures. This finding is consistent with previous research (Deschenes and Moretti, 2009).

As Figure 6 suggests, the impacts of the rising temperatures are not significantly different between men and women. However, in the weekly exposure horizon, the effect on men is



(a) Weekly Temperature Exposure Window (b) Monthly Temperature Exposure Window

Figure 6: Estimates of Impact of Daily Temperature on Log Mortality Rate, by Gender

Notes: The plotted lines report coefficient estimates for each temperature bin. Each marker indicate the impact of a single day in each of the 9 temperature bins, relative to the impact of a day in 0-5 °C reference bin, on log mortality. Dashed lines represent the 95% confidence interval of the estimates. Panel a and panel b are driven from the equation (1) and equation (2), respectively.

marginally higher (Figure 6a).

Table 8 reports estimates from alternative specifications. Humidity, like temperature, is an essential determinant of mortality (Barreca, 2012). We divide relative humidity into four categories[5]. Subsequently, we include relative humidity controls in equation (1) and equation (2). Column 2 and column 5 in Table 8 represent our estimates after controlling for humidity in equation (1) and equation (2), respectively. Furthermore, we use maximum daily temperature instead of average daily temperature in our baseline models (columns 3 and 6, Table 8). The difference between estimated coefficients in the weekly exposure window is marginal. In the monthly exposure window, however, there is a considerable increase in high temperatures' effects when we use maximum daily temperature instead of average daily temperature.

[5]These four groups are "0%-25%," "25%-50%," "50%-75%", "and 75%-100%."

Table 6: Estimates of the Impact of Different Average Temperatures on Log Mortality Rate in Different Age Categories on a Weekly Time Frame

	(1) All ages	(2) Infant	(3) Child & Teen	(4) Adult	(5) Middle Age	(6) Senior
<-5 °C	-0.00305	-0.0107	-0.00545	0.00251	-0.00542	0.00456
	(0.00477)	(0.0104)	(0.0115)	(0.00907)	(0.0104)	(0.00464)
-5-0 °C	-0.0143***	-0.0171**	-0.0349***	-0.0116**	-0.00280	-0.00650***
	(0.00301)	(0.00706)	(0.00688)	(0.00481)	(0.00486)	(0.00182)
5-10 °C	0.00137	0.00226	-0.00608	0.00230	0.00207	0.00658***
	(0.00190)	(0.00511)	(0.00537)	(0.00376)	(0.00274)	(0.00134)
10-15 °C	0.0118***	0.0105**	0.00623	0.0142***	0.0116***	0.0163***
	(0.00200)	(0.00461)	(0.00604)	(0.00409)	(0.00306)	(0.00191)
15-20 °C	0.0146***	0.0137**	0.00897	0.0184***	0.0138***	0.0185***
	(0.00231)	(0.00594)	(0.00567)	(0.00496)	(0.00363)	(0.00208)
20-25 °C	0.0210***	0.0210***	0.0191***	0.0282***	0.0194***	0.0183***
	(0.00254)	(0.00620)	(0.00660)	(0.00561)	(0.00383)	(0.00224)
25-30 °C	0.0258***	0.0245***	0.0246***	0.0321***	0.0243***	0.0244***
	(0.00290)	(0.00765)	(0.00686)	(0.00647)	(0.00420)	(0.00277)
30-35 °C	0.0259***	0.0210**	0.0236***	0.0352***	0.0252***	0.0254***
	(0.00356)	(0.00910)	(0.00834)	(0.00852)	(0.00486)	(0.00351)
>35 °C	0.0218***	0.0167	0.00429	0.0326***	0.0288***	0.0269***
	(0.00460)	(0.0111)	(0.0105)	(0.0103)	(0.00682)	(0.00406)
R^2	0.888	0.273	0.321	0.531	0.440	0.317
N	123412	22660	24188	25072	25639	25853

Standard errors in parentheses

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

Notes: Standard errors clustered by province-by-demography are reported in parentheses. The dependent variable is log mortality rate. The duration of the temperature exposure window is one week. All the coefficients are estimates from equation (1). Each column reports the estimated coefficients of different age categories. Each column includes month-year fixed effects, province-by-demography fixed effects, and precipitation controls. People dying at the ages of "0", "1-19", "20-39", "40-59", "and above 60" are categorized as "Infant," "Child&Teen," "Adult," "Middle Age," and "Senior," respectively.

Table 7: Estimates of the Impact of Different Average Temperatures on Log Mortality Rate in Different Age Categories on a Monthly Time Frame

	(1) All ages	(2) Infant	(3) Child & Teen	(4) Adult	(5) Middle Age	(6) Senior
<-5 °C	0.000306	-0.00309	0.00216	-0.00553	0.00207	0.00602**
	(0.00274)	(0.00517)	(0.00684)	(0.00612)	(0.00516)	(0.00245)
-5-0 °C	-0.00593***	-0.00852	-0.0184***	0.000782	-0.00168	-0.00195*
	(0.00198)	(0.00532)	(0.00446)	(0.00283)	(0.00222)	(0.00107)
5-10 °C	-0.000739	0.000504	-0.00432	-0.000582	-0.000536	0.00120*
	(0.00117)	(0.00330)	(0.00329)	(0.00166)	(0.00133)	(0.000666)
10-15 °C	0.00280**	0.00531*	0.00179	0.00362*	0.000564	0.00274***
	(0.00121)	(0.00301)	(0.00376)	(0.00204)	(0.00131)	(0.000680)
15-20 °C	0.00312**	0.00813**	0.00142	0.00326	0.000306	0.00245***
	(0.00146)	(0.00380)	(0.00394)	(0.00197)	(0.00165)	(0.000838)
20-25 °C	0.00467***	0.0104**	0.00516	0.00509**	0.000669	0.00207**
	(0.00171)	(0.00435)	(0.00483)	(0.00247)	(0.00184)	(0.000917)
25-30 °C	0.00539***	0.0122**	0.00654	0.00474	0.00134	0.00213**
	(0.00200)	(0.00510)	(0.00542)	(0.00294)	(0.00218)	(0.000953)
30-35 °C	0.00532**	0.0126**	0.00648	0.00546	0.000393	0.00165
	(0.00242)	(0.00619)	(0.00687)	(0.00358)	(0.00243)	(0.00121)
>35 °C	0.00377	0.0135*	0.000875	0.00330	0.000450	0.000776
	(0.00289)	(0.00737)	(0.00767)	(0.00441)	(0.00336)	(0.00134)
R^2	0.938	0.390	0.488	0.771	0.753	0.733
N	129460	25804	25896	25920	25920	25920

Standard errors in parentheses

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

Notes: Standard errors clustered by province-by-demography are reported in parentheses. The dependent variable is log mortality rate. The duration of the temperature exposure window is one month. All the coefficients are estimates from equation (2). Each column reports the estimated coefficients of different age categories. Each column includes month-year fixed effects, province-by-demography fixed effects, and precipitation controls. People dying at the ages of "0", "1-19", "20-39", "40-59", "and above 60" are categorized as "Infant," "Child&Teen," "Adult," "Middle Age," and "Senior," respectively.

Table 8: Alternative Estimates of the Impact of Different Average Temperatures on Log Mortality Rate

	Weekly Exposure Window			Monthly Exposure Window		
	(1)	(2)	(3)	(4)	(5)	(6)
<-5 °C	-0.00305	-0.00312	-0.0346*	0.000306	0.000347	-0.0193
	(0.00477)	(0.00478)	(0.0198)	(0.00274)	(0.00275)	(0.0125)
-5-0 °C	-0.0143***	-0.0144***	0.00369	-0.00593***	-0.00591***	0.00468*
	(0.00301)	(0.00301)	(0.00535)	(0.00198)	(0.00198)	(0.00283)
5-10 °C	0.00137	0.00149	0.00683**	-0.000739	-0.000814	0.00374**
	(0.00190)	(0.00187)	(0.00303)	(0.00117)	(0.00116)	(0.00183)
10-15 °C	0.0118***	0.0119***	0.00788***	0.00280**	0.00263**	0.00310**
	(0.00200)	(0.00196)	(0.00286)	(0.00121)	(0.00120)	(0.00158)
15-20 °C	0.0146***	0.0149***	0.0199***	0.00312**	0.00281*	0.00636***
	(0.00231)	(0.00224)	(0.00294)	(0.00146)	(0.00144)	(0.00159)
20-25 °C	0.0210***	0.0214***	0.0226***	0.00467***	0.00421**	0.00738***
	(0.00254)	(0.00246)	(0.00313)	(0.00171)	(0.00167)	(0.00179)
25-30 °C	0.0258***	0.0262***	0.0280***	0.00539***	0.00478**	0.00864***
	(0.00290)	(0.00278)	(0.00337)	(0.00200)	(0.00196)	(0.00197)
30-35 °C	0.0259***	0.0260***	0.0331***	0.00532**	0.00456*	0.00955***
	(0.00356)	(0.00334)	(0.00366)	(0.00242)	(0.00238)	(0.00212)
>35 °C	0.0218***	0.0219***	0.0357***	0.00377	0.00292	0.00975***
	(0.00460)	(0.00440)	(0.00424)	(0.00289)	(0.00286)	(0.00254)
R^2	0.888	0.888	0.888	0.938	0.938	0.938
N	123412	123412	123412	129460	129460	129460

Standard errors in parentheses

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

Notes: Standard errors clustered by province-by-demography are reported in parentheses. The dependent variable is log mortality rate. In columns 1-3, the duration of the temperature exposure window is one week. In columns 4-6, the duration of the temperature exposure window is one month. Each column includes month-year fixed effects, province-by-demography fixed effects, and precipitation controls. Columns 1 and 4 report our baseline estimates derived from equation (1) and equation (2), respectively. We include humidity controls in columns 2 and 4 in addition to our baseline estimates. Models implemented in columns 3 and 6 use maximum daily temperature instead of average daily temperature in equation (1) and equation (2), respectively.

5 Conclusion

In this paper, we estimate the effects of rising temperatures on mortality in a developing country, Iran, which is more fragile to weather shocks compared to developed countries. Our rich data set, consisting of weekly morality, enables us to compare the effects of temperature variation on mortality, in a very short-run horizon and longer exposure windows. Our preferred models show that high temperatures have considerable and mainly statistically significant impacts on mortality rate in weekly and monthly temperature exposure windows. For instance, in a monthly temperature exposure window, an additional day in 30-35 °C, significantly increases the mortality rate by 0.53%, relative to the impact of an extra day in 0-5 °C. The estimated coefficient becomes larger when we use the weekly temperature exposure window. For example, in the weekly temperature exposure window, an extra day in 30-35 °C, significantly increases the mortality rate by 2.59%, relative to the impact of an additional day in 0-5 °C. These findings are in line with Burgess et al., 2017, both suggesting that hot days are deadlier in developing countries.

Furthermore, our weekly data set enables us to estimate the effects of rising temperatures on mortality rate in a very short horizon. We provide further evidence that the harvesting effect plays a prominent role in estimating the impact of temperature variation on mortality rate. Our empirical models suggest that the impacts of rising temperatures on mortality rate are noticeably larger when the temperature exposure window is a week compared to a month. The harvesting effect can explain this contrast. The mortality rate drop in the following weeks can compensate for the spike in deaths after a certain weather shock. In several cases, we confirm that high temperatures only change the timing of deaths for a few days or weeks. This finding is consistent with Deschenes and Moretti, 2009. Still, our estimates are significant when we implement a longer time horizon.

Temperature variation's impacts on mortality rate are not identical among different demographic groups. Our results show large and significant effects on all demographic groups in the weekly horizon. Seniors and infants are more vulnerable and most affected by tem-

perature variation. However, we indicate that high temperatures affect the mortality rate of senior and middle-aged individuals through the harvesting effect, and the estimated coefficients related to the mentioned impacts are negligible and statistically insignificant in the monthly temperature exposure horizon. Moreover, this research proposes that infants, adults, children and teenagers are more vulnerable to climate shocks. Adults, who are generally have better health condition, are at risk, because they are more exposed to direct weather shocks, unlike senior and middle-aged people who spend more time on indoor activities.

The more human being experiences scorching days more frequently, the more essential to evaluate their effects on human health and mortality. As the hot days lead to a substantial increase in mortality rate in developing countries, policymakers have to take into serious consideration the weather-driven impact of rising temperatures on human health. Since these impacts are dissimilar among different age groups, policymakers may need to prioritize certain groups, regarding policies with preservation targets. Our Analysis implies that policymakers have to consider adults as one of the most affected groups.

In a warming world where four-fifth of its population lives in developing economies (UNCTAD, 2015), it is crucial to assess and address the dire consequences of rising temperatures in these countries. In contrast to developed countries, such as the US, where means of adaptation like air conditioning are broadly available, the mortality of people living in developing economies may be largely affected by rising temperatures and this paper reveals one of these affected countries, Iran. In order to address this issue policymakers have to take adequate actions for a better adaptation.

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A Appendix

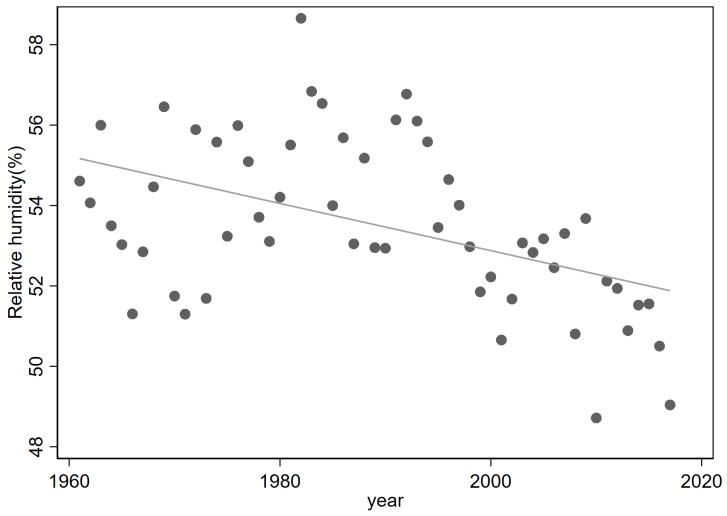
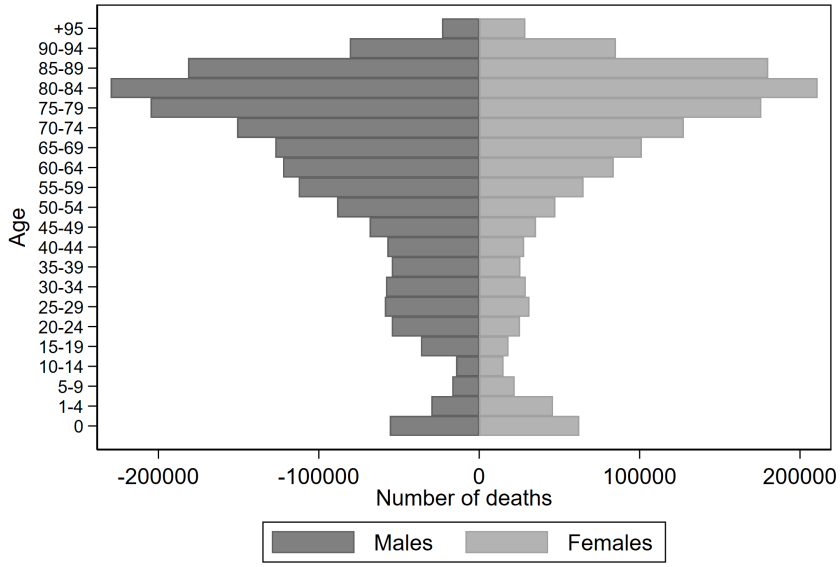


Figure A.1: Relative Humidity in Iran

Notes: The figure shows Iran's annual relative humidity [in percentage] from 1961 to 2018. Here we only use the data from 16 weather monitoring stations established before 1961 and do not have any missing daily reports from 1961-2018.



Source: National Organization for Civil Registration (NOCR), 2009-2017

Figure A.2: Total Recorded Deaths in Iran, from 2009 to 2017

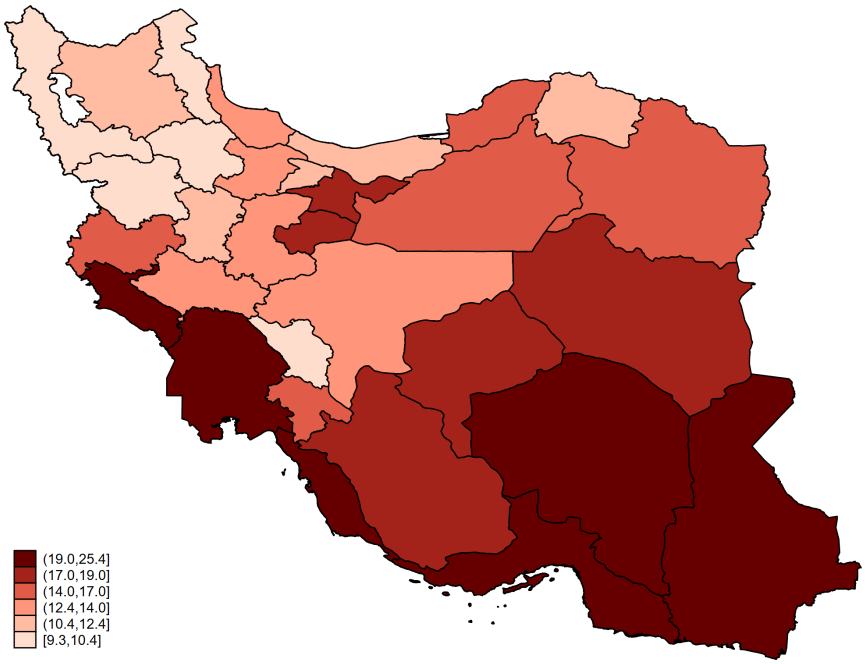


Figure A.3: Average Annual Temperature Map from 1997 to 2017

Notes: Figure shows province-level average annual temperature [in Celsius degrees] in Iran, from 1997 to 2017.

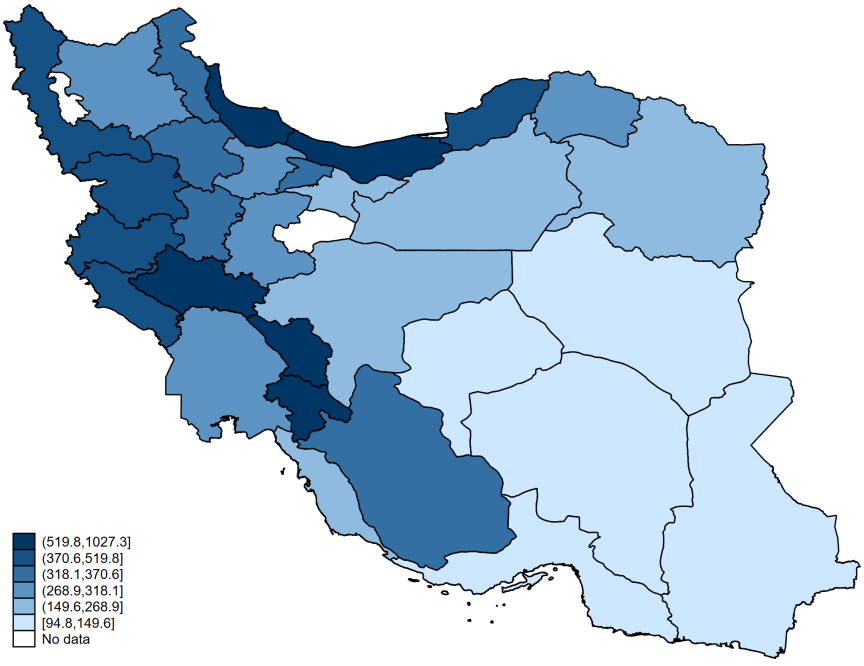


Figure A.4: Average Annual Precipitation Map from 1997 to 2017

Notes: Figure shows province-level average annual precipitation [in millimeters] in Iran , from 1997 to 2017.



Figure A.5: Stations Established Before 1961 Without Any Missing Daily Reports

Notes: The graph shows weather monitoring stations which have established before 1961 and do not have any missing daily reports from 1961 to 2018.

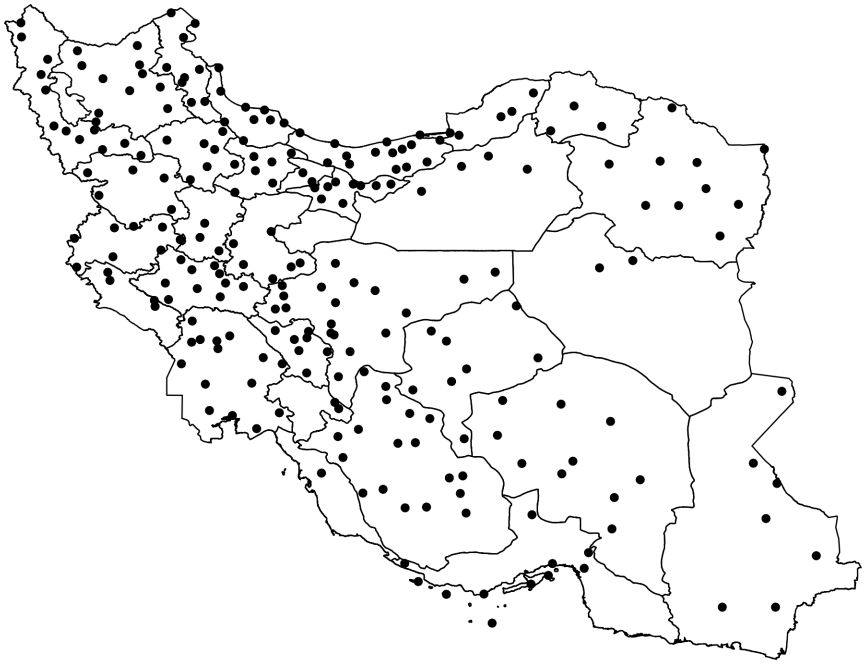


Figure A.6: Stations Established Before 2009 Without Any Missing Daily Reports

Notes: The graph shows the weather monitoring stations which have established before 2009 and do not have any missing daily reports from 2009 to 2018.

Table A.1: Estimates of the Impact of Daily Temperature on Log Mortality Rate, by Gender

	Weekly Exposure Window		Monthly Exposure Window	
	(1) Female	(2) Male	(3) Female	(4) Male
<-5 °C	-0.00699	0.000972	0.00249	-0.00187
	(0.00743)	(0.00596)	(0.00396)	(0.00374)
-5-0 °C	-0.0167***	-0.0119***	-0.00686**	-0.00500**
	(0.00489)	(0.00350)	(0.00319)	(0.00232)
5-10 °C	-0.00239	0.00519**	-0.00145	-0.0000188
	(0.00270)	(0.00239)	(0.00176)	(0.00147)
10-15 °C	0.00883***	0.0148***	0.00281	0.00280*
	(0.00269)	(0.00263)	(0.00179)	(0.00154)
15-20 °C	0.00995***	0.0193***	0.00290	0.00333
	(0.00303)	(0.00317)	(0.00195)	(0.00212)
20-25 °C	0.0168***	0.0252***	0.00479**	0.00455*
	(0.00336)	(0.00351)	(0.00234)	(0.00244)
25-30 °C	0.0212***	0.0304***	0.00564**	0.00514*
	(0.00383)	(0.00413)	(0.00264)	(0.00296)
30-35 °C	0.0219***	0.0299***	0.00635*	0.00429
	(0.00467)	(0.00517)	(0.00324)	(0.00358)
>35 °C	0.0182***	0.0255***	0.00552	0.00201
	(0.00606)	(0.00662)	(0.00380)	(0.00431)
R^2	0.884	0.893	0.931	0.947
N	61267	62145	64728	64732

Standard errors in parentheses

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

Notes: Standard errors clustered by province-by-demography are reported in parentheses. The dependent variable is log mortality rate. In columns 1 and 2, the duration of the temperature exposure window is one week. In columns 3 and 4, the duration of the temperature exposure window is one month. Each column includes month-year fixed effects, province-by-demography fixed effects, and precipitation controls.