The Distributional Effects of Climate Change: Evidence from Iran*

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Abstract

Climate change has a heterogeneous effect across poor and rich households due to differences in vulnerabilities and exposure. Yet, there are very few papers that provide estimates on the magnitude of climate impact across the income distribution. In this paper, we combine 21 rounds of household expenditure and income survey from 1998 to 2018 in Iran to construct a large sample of rural and urban households. Using within district variations in temperature, we show that a one Celsius degree increase in annual temperature respectively leads to an 8.1 and 4.7 percent decrease in rural and urban per capita expenditure. We find that the impact is twice the average effect for the poorest decile. Furthermore, we provide evidence that available household resources that determine vulnerabilities play a more important role than the difference in exposure to climate change. Our findings suggest that compensatory policies should target the poorest households as poverty is a stronger determinant of impact compared to being an agricultural earner or residing in already hot areas.

Keywords: Climate Change, Expenditure distribution, Vulnerability, Poverty
JEL Codes: Q51, Q54, Q12, I32, D31

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1 Introduction

The recent evidence on climate change with projected dire consequences for human life has spurred a range of studies that try to estimate the economic implications of this global phenomenon (Dell et al. 2014; Burgess et al. 2017). Current scenarios predict changes in rainfall and warmer temperatures across the globe in addition to changes in frequency and intensity of extreme events (IPCC 2018 and Auffhammer 2018). Agricultural production, economic growth, health, and conflict are a sample of many outcomes studied in the vast literature[1]. The focus of this literature has been on average outcomes. But the climate impact is likely to vary across individuals due to differences in exposure, vulnerability, and available adaptation strategies (López-Feldman and Rivera 2018; Leichenko and Silva 2014). First, it is well-known that changes in temperature and rainfall as a result of climate change are distributed unevenly across regions (Seneviratne et al. 2016). Second, the climate sensitivity of different types of livelihoods is likely to differ. Agriculture is thought to be the most sensitive income source, while industrial activities are less sensitive. Third, households with different initial endowments (financial, human and other types of capital) have different adaptation capacities. Fourth, climate effects might be non-linear. In other words the existing environmental conditions could shape the impact of a given change in temperature and rainfall.

Compensatory policies should target households who are likely to receive greater impacts and focus on mechanisms that are most effective in combating climate impacts. However, the existing evidence on the heterogeneity of climate impact and the mechanisms creating such heterogeneity is far from conclusive (Hsiang et al. 2019 and López-Feldman and Rivera 2018). Some macro studies look at country groups to shed light on the heterogeneity of impact. For example, Dell et al. (2012) find a significant impact of temperature increases only for poor countries. However, Country-level aggregates miss out within country heterogeneity that

[1]See Dell et al. (2014) and Auffhammer (2018) for a complete review. For the impact on aggregate output and economic growth see Nordhaus (2006), Mendelsohn et al. (2007), Dell et al. (2009), Dell et al. (2012) and Kalkuhl and Wenz (2020); for the impact on agricultural production see Deschênes and Greenstone (2007), Guiteras (2009), and Schlenker and Roberts (2009); for the effect on labor productivity and labor supply see Hsiang (2010), Graff Zivin and Neidell (2014); for the effect on health and mortality see Deschênes and Greenstone (2011), Burgess et al. (2017); for the impact on conflict and crime see Miguel et al. (2004); Burke et al. (2009); and Jacob et al. (2007)

might be even more important than cross country differences. Furthermore, it is very difficult to separate the mechanisms that create the heterogeneity. The poor might receive a greater impact from climate change due to higher vulnerability (Dell et al. 2012) or unfavorable initial environmental conditions, e.g. higher temperatures (Hsiang and Meng 2015). Separation of these two channels matter for policy design.

Household-level data allows a richer analysis and is potentially very useful in disentangling various mechanisms. However, the literature here is nascent (López-Feldman and Rivera 2018). A relevant part of this literature is the studies that look at the impact of climate change on income inequality and poverty. Skoufias and Vinha (2013) provide evidence on the negative impact of weather shocks on food and non-food household consumption in rural Mexico. They observe that households' ability to smooth out weather shocks depends on the climate of the region and the timing of the shock within the agricultural year. Hertel et al. (2010) use micro data on household economic activity within 15 developing countries and a general equilibrium global trade model[2] to explore how changes in agricultural activity affects poverty. They show that climate-induced food price hikes could be large, but the poverty impact depends on the main income source of the households. Jacoby et al. (2011) show that climate change has a heterogeneous impact on poverty across regions of India. In this study, increases in food prices is an important compensatory mechanism for rural farmers which adversely affects poor urban households.

A related literature looks at the impact of natural disasters across the income distribution. Climate change is likely to increase the frequency and intensity of natural disasters with heterogeneous effects across households. Wineman et al. (2017) show that the negative effect of weather extremes (especially droughts) on household income depends on access to credit and the level of income diversification. Yamamura (2015) looks at the impact of disasters on income inequality in a panel of countries and shows a negative short run impact on inequality. There is, however, no discernible long run effect. Pleninger (2020) studies US counties and finds only an impact on middle income households.

[2]the Global Trade Analysis Project, or GTAP

This paper uses a rich dataset to investigate the heterogeneous impact of climate change across households. We create a pseudo-panel by linking 21 rounds of Household Expenditure and Income Survey (HEIS) in Iran between 1998 and 2018 at district-level. HEIS provides a comprehensive picture of household income and expenditure which allows us to have a careful look at the heterogeneity of climate impact across various subgroups. We combine HEIS with daily temperature and precipitation to construct measures of climate variability that include both averages and extreme weather events.

The classic approach uses cross-sectional data (for example, Mendelsohn et al. 1994; Gallup et al. 1999; Sachs 2003; Nordhaus 2006; and Dell et al. 2009) to attribute part of the difference in economic performance to geographical differences in temperature and precipitation. The challenge with this approach is omitted variable bias. Instead, we rely on within district variation in weather to identify the impacts (Auffhammer et al. 2006 and Deschênes and Greenstone 2007). District fixed effects control for confounding variables that are fixed over time, such as distance from the coast, land gradient, elevation, soil quality, and institutions that are likely to be correlated with outcomes and weather. We also allow for district-specific quadratic trends to take care of any time-variant unobservable characteristics that might be correlated with weather and incomes.

We employ our estimation strategy to first look at the overall impact of climate variability. According to our preferred specification, a one Celsius degree increase in annual temperature and a 100 mm increase in annual precipitation are respectively associated with an 8.1 percent decrease and 1.5 percent increase in annual per capita expenditure of rural households. We also find a statistically significant negative impact of extremely hot days. Interestingly, the average effects are smaller but *significant* for urban households suggesting presence of mechanisms other than loss of agricultural produce. These results are fairly robust to several specification and sample checks.

Since the rainfall impacts are generally smaller, we focus on temperature effects in the second part of our results. Here, we estimate separate effects for income deciles in urban and rural areas. The effect of a one degree increase in temperature is 15 percent for the poorest

rural decile while it is almost zero for the richest decile. A similar pattern holds for urban deciles. Interestingly, the urban deciles always receive a smaller impact than the comparable rural deciles.

We further explore the reasons for the higher climate impact on the poor by investigating two heterogeneities. First, we look at the geographical dispersion of deciles across cold and hot areas. Hot areas show greater sensitivity to temperature increases. At the same time we see a higher share of poorer households in hot areas. Interestingly, the impact of a one degree increase in temperature is similar for poor deciles across hot and cold regions. The gap only shows when we look at decile above the median. This suggests poverty is a key determinant of climate impact. Initial climate conditions only matter for the richer deciles. Second, we compare agricultural and non-agricultural earners. Here, we observe a greater impact for agricultural earners but the gap between agricultural and non-agricultural households is uniform across deciles of income distribution. Our results suggest that reliance on climate sensitive livelihoods and lack of financial resources are more important than starting climate conditions.

Our paper makes three contributions to the literature on the impact of climate change. First, our findings corroborate and extend the nascent literature that finds a stronger impact of temperature on poor countries (e.g. Dell et al. 2014 and Burgess et al. 2017). The richness of our data allows us to look at deciles of the expenditure distribution. The temperature impact on the poorest decile is about twice as large as the average effect. Ignoring this heterogeneity results in poorly targeted climate policies.

Second, we explore two important explanations for why poorer households receive a greater impact from climate variation. Impact is a function of vulnerability and exposure to shocks. Poor households might have higher exposure to climate shocks. For example, they might engage in climate sensitive activities like agriculture. They might also have higher vulnerability that prevents them from combating adverse shocks. Our results support the idea that individual vulnerabilities are what matters the most. After controlling for exposure by looking within agricultural earners in the same climatic conditions we observe a much greater role for

available household resources in reducing the climate impact. In other words, we always see a sharp reduction in climate impact as we move up the expenditure distribution, but the change in impact is smaller when we change exposure by looking at the gap between agricultural and non-agricultural households or cold and hot regions. This is a novel finding and supports a targeted climate mitigation policy that gives more weight to existing household resources and treats specific areas and occupations slightly differently.

Third, we show that panel model estimates of climate change could be comparable to cross-sectional estimates in magnitude. We conjecture that the aggregation bias in existing macro-level panel estimates is responsible for the small size of effects. Since we map outcomes and weather variation at the district-level we have a finer correspondence between what matters for outcomes and hence get larger effects. A related point here is the heterogeneity of climate impact across rural and urban areas which was largely ignored in previous studies. Rural areas might have greater exposure to climate shocks. Combining all regions in one regression masks this heterogeneity and results in smaller magnitudes.

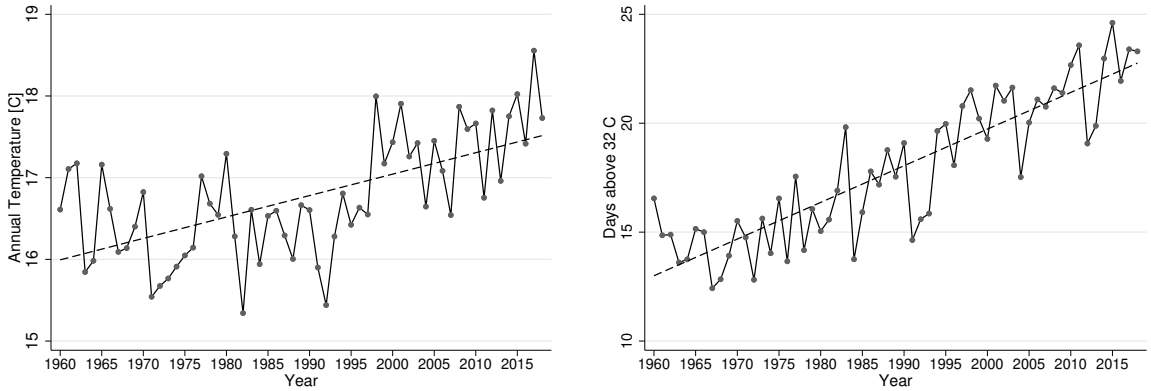
The rest of the paper is organized as follows. In the next section, we provide a brief overview of the Iranian context and explain the data sources used in the analysis. Section 3 outlines our empirical strategy for the identification of temperature effects. Section 4 looks at the main results and presents several robustness checks. A final section provides discussion and conclusion.

2 Context and Data

In this section, we first describe the Iranian context and then explain the two datasets used in this research. Finally, we provide a description of the data.

2.1 Context

Iran is a country in West Asia bordering the Persian Gulf to the South and the Caspian Sea to the North. More than 80% of the country is located in arid and semi-arid zones (Amiri et al. 2010). In the past 60 years, Iran has experienced an increase of about 0.85°C in surface



(a) Annual Temperature

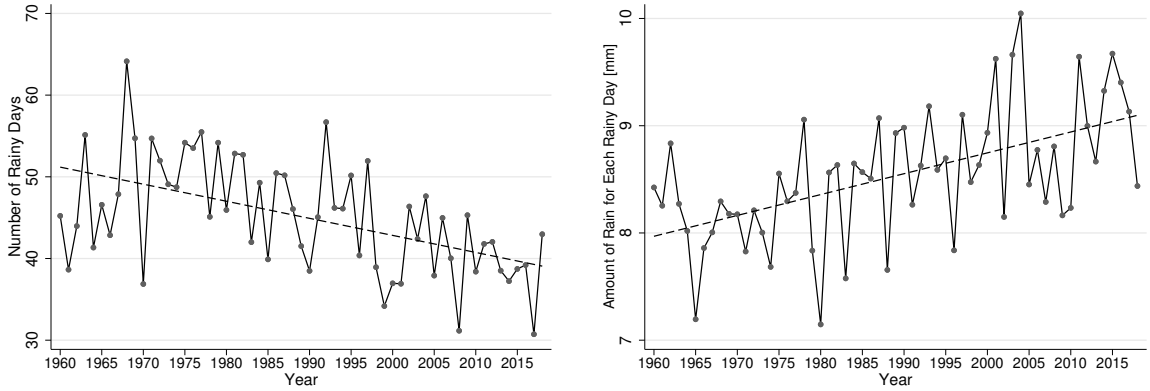
(b) N. of Days Above 32°C

Figure 1: Long-term temperature trend in Iran

Notes: Panels A and B show average annual temperature and number of days above 32°C in Iran from 1960 to 2018, respectively. Here we only use the data from 33 weather stations that have data for more than 95% of the entire period (1960-2018).

temperatures which is slightly faster than the increase in average global temperature (Figure 1). The number of extremely hot days (days with average temperature above 32°C) has almost doubled in the past 60 years (Figure 1). Furthermore, average number of rainy days in a year has dropped by about 20% in this period, but the amount of rainfall for each rainy day has increased[3] (Figure 2). Figure 3 shows the map of average temperature in districts of Iran from 1998 to 2018. The average annual temperature varies from 7°C in the coolest district to 28°C in the warmest one. North-west part of Iran is the coolest area and the south and central areas are the warmest. There is a tight negative correlation between average household income and temperature. Figure 4 shows district-level distribution of total per capita expenditure for urban (Panel A) and rural (Panel B) households. Both maps show that hotter areas are poorer. In other words, households living near the eastern and western borders are on average poorer than central and northern ones.

[3]Total precipitation amount experienced a slight decrease in this period.



(a) N. of Rainy Days

(b) Average Rainfall for each Rainy Day

Figure 2: Long-term precipitation trend in Iran

Notes: Figure shows average number of rainy days and average rainfall for each rainy day from 1960 to 2018 in Iran in panels A and B, respectively. Here we only use the data from 33 weather stations that have data for more than 95% of the entire period (1960-2018).

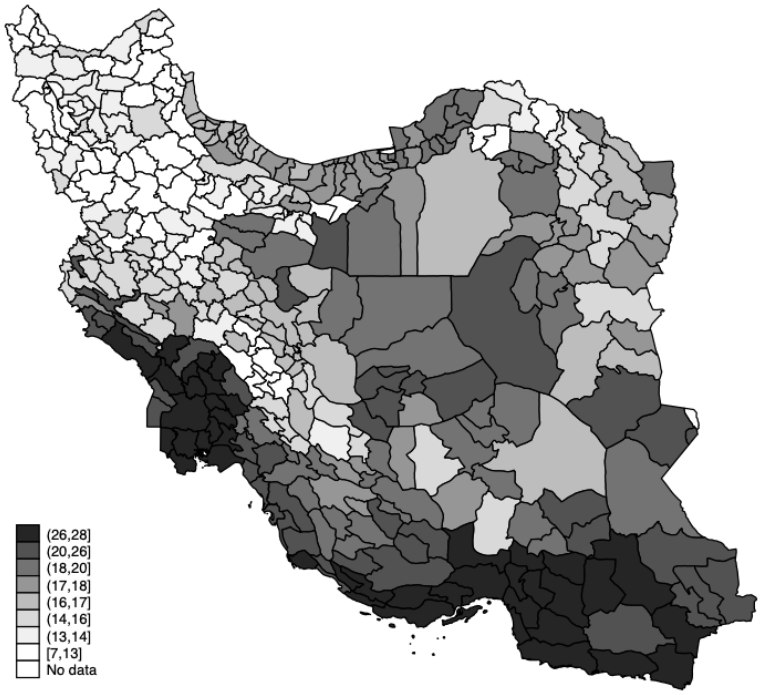
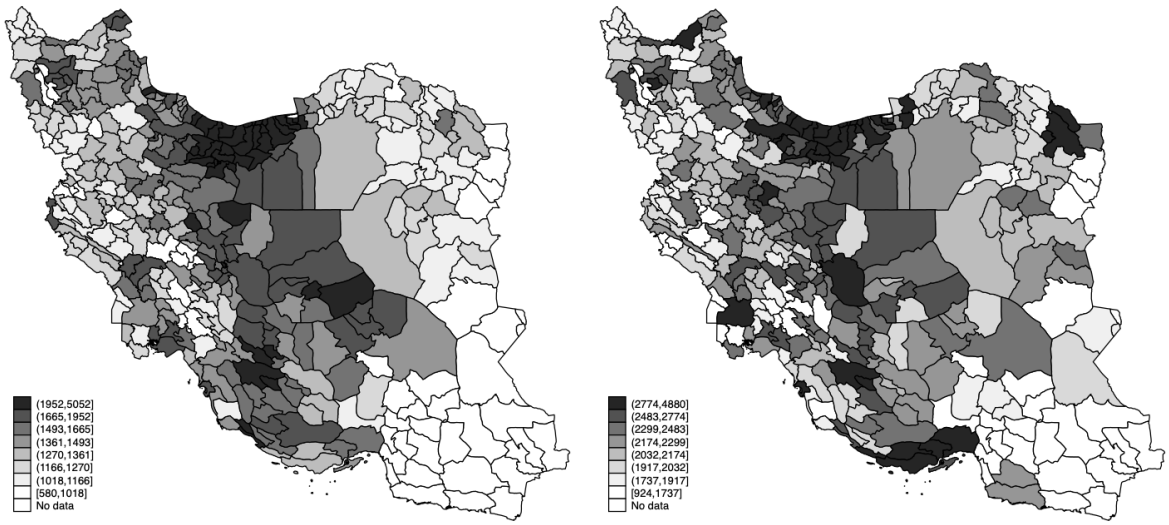


Figure 3: Average annual temperature map from 1998 to 2018

Notes: Figure show district-level annual temperature average [in Celsius degrees] from 1998 to 2018 in Iran.



(a) Rural (b) Urban

Figure 4: Average annual income per capita map from 1998 to 2018

Notes: Panels A and B show district-level average real per capita income from 1998 to 2018 in Iran. We use CPI 2011 provided by SCI to realize the income data and use exchange rate USD 1 = IRR 13,568. Data source: HEIS.

2.2 Household Expenditure and Income Survey

Household Expenditure and Income Survey (HEIS) is an annual household budget survey conducted by the Statistical Center of Iran (SCI). It contains detailed information on more than 300 expenditure items and incomes from various sources for rural and urban households. There are between 20,000 to 40,000 households in each round of the survey. While the survey was conducted from 1984 onward, the sampling weights and district codes are unavailable prior to 1997. Therefore, we focus our analysis on the years from 1998 to 2018. HEIS also contains some individual characteristics such as family size, age, education, and gender as well as household residential stats such as home ownership, number of rooms, access to infrastructure (electricity, piped gas, tap water), home appliances (refrigerator, AC, etc.), and cooking and heating fuels.

Our main dependent variable is annual real per capita household expenditure which is constructed from detailed expenditure items categorized in 12 main groups of food, housing (rent and utilities), cloth, health, transportation, communication, furniture, amusement, education,

hotel and restaurant, durable goods, and other goods. Expenditure is a better measure of household welfare because income is often understated in household budget surveys. Furthermore, expenditure shows the flow of goods and services consumed by the household whereas income might be saved to create a buffer stock. Therefore, it is a better reflection of material well-being. Nevertheless, as a robustness we run the main regressions with real per capita household income as well. Household income is coming from sources of wage, self-employed agricultural and non-agricultural income and other sources of income (rent, retirement, home production, cash transfers, interest, direct transfers from other households).

We use Consumer Price Index (CPI) of urban and rural areas with base year of 2016 provided by SCI to realize the nominal income and expenditure. In addition, we divide the total income and expenditure of households to family size to provide the total income and expenditure per capita. Furthermore, we multiply the expenditure of households on all the categories except education and durable goods by 12, because the expenditure in last month is asked in the questionnaire, to generate the annual data. Expenditure on education and durable goods and also income data are originally at the annual level. To construct expenditure deciles, we separately sort rural and urban households in each survey round by per capita expenditure and split the population to ten equal groups (deciles). In this exercise we take into account household weights to make the sample representative of the whole country. Another point is that HEIS corresponds to the Persian calendar which starts on March 21 of the Gregorian calendar. For exposition of yearly figures we simply use the Gregorian year that has 9 months overlap with the Persian year.

2.3 Weather Data

Our weather data is provided by National Drought Warning and Monitoring Center (NDWMC) and Iran Meteorological Organization (IMO). This data contains interpolated district-level daily measurements of maximum and minimum temperature [in Celsius degrees], and precipitation [in mm] from 1959 to 2018[4]. We define daily temperature as simple average of

[4]We use district-level interpolated data provided by NDWMC as our main weather dataset but as a robustness check, we use station level data provided by IMO, too. Number of stations has been increasing

maximum and minimum temperatures during a day. Annual average temperature is defined as the average of daily temperatures during all days in a year. Similarly, we sum up all daily precipitation amounts during a year to provide annual precipitation[5].

In addition to annual temperature and precipitation, extreme weather events can affect the economy (Dell et al. 2014). We define "extremely hot days" as the number of days with a daily temperature that exceeds 32°C within a year (similar to Deschênes and Greenstone 2011 and Barreca 2012) and "heavy rain" as the number of days having greater than the 99th percentile of daily precipitation. But these variables have very high correlations with annual temperature and precipitation (1) and if included at the same time in the regressions may lead to multicolinearity. Therefore, we use a relative definition for extreme temperature and rainfall events. Specifically, we define the "number of relatively hot days" and the "number of relatively heavy rains" by counting days above the district specific 99th percentile of these variables. The percentiles are calculated based on 21 years of data for each district. These new defined variables do not have high correlations with annual temperature and precipitation (Table 1). Therefore, we can include them as separate regressors to control for extreme weather events. A relative definition of extremes is also more appropriate as locals might adapt to enduring conditions and given the climate diversity across districts in Iran, it is better to gauge extremes based on each district's long-term averages. We use annual temperature as our main weather variable and use annual precipitation, number of relatively hot days and number of relatively heavy rains as control variables.

Another important point to be considered is the increase in the number of provinces and districts in Iran during our study period. Number of districts in Iran has increased from 281 districts in 1998 to 429 districts in 2018[6]. Some districts are divided into two or three new districts. Entire the paper, we use the administrative borders of 1998 which is the first year of our study and avoid the divisions for both of the datasets.

from about 30 stations in 1959 to about 450 stations in 2018 (Figure A.1 in Appendix). To avoid potential endogeneity resulting from station establishment date, here we keep 160 stations up until to 1998.

[5]The probable increase in accuracy of precipitation measuring devices over time may lead to an invalid trend in annual precipitation. We replace all less than 1 mm daily precipitation amounts to zero to avoid this.

[6]Number of provinces has increased from 28 to 31 provinces during the same period, too.

Table 1: Correlations of weather variables

VARIABLES	Temperature (1)	Precipitation (2)	Rel Hot Days (3)	Rel Heavy Rains (4)	Above 32°C (5)	P99 PCP (6)
Temperature	1					
Precipitation	-0.23	1				
Rel Hot Days	0.06	-0.06	1			
Rel Heavy Rains	-0.03	0.23	-0.11	1		
Above 32°C	0.87	-0.29	0.08	-0.03	1	
P99 PCP	-0.16	0.94	-0.06	0.33	-0.21	1

Notes: Table shows correlations of weather variables. Above 32°C is number of days in a year for a district that daily temperature is above 32°C. P99 PCP is percentile 99 of daily precipitation [in mm] in a year for a district.

2.4 Data Description

Table 2 shows summary statistics of our data after merging HEIS and weather data from 1998 to 2018. We report overall mean and standard deviation of variables in columns (1) and (5) respectively for rural and urban areas. Total number of households in the HEIS data is about 640,000 (32,000 households for each year on average) and more than half of the sample is from rural areas. Weather conditions seem to be similar across urban and rural areas. However, rural areas are generally poorer and have more farming activities. Average real per capita income and expenditure for rural households are respectively 1,384 and 1,455 USD. Income could be smaller than zero for businesses with costs greater than revenue in a year. Per capita income for urban households is around 800 USD (60%) higher than that of rural households. Households residing in urban areas might be engaged in agriculture as well. We see 8.2 percent of urban households rely on agricultural income either in the form of wage or self-employment[7]. In columns (2) to (4) we report statistics for the first, fifth, and tenth income deciles. The poorest decile seems to live in slightly hotter and drier areas. The ratio of average per capita expenditure for the richest to poorest decile is 5.5 in rural areas and 6.9 in urban areas.

[7]Definition of rural and urban areas in Iran is an official definition by the government and is not related to agricultural workers. Urban areas are the communities which have municipality and municipality could be established for areas with more than 5,000 (10,000 recently) of population. Then, there are some areas with more than 5,000 of population (then have a municipality and defined as urban area) but many people work in agricultural sector. To investigate the effects on pure urban areas (without agricultural workers), we restrict the urban areas to cities with less that 20, 10, and 5 percent of agricultural workers and in a stricter one to just 7 biggest cities in Iran (Table A.1) in Appendix

Table 2: Summary Statistics

	Rural				Urban			
	Total	1th	5th	10th	Total	1th	5th	10th
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Temperature [°C]	16.5	16.8	16.4	16.1	16.3	16.6	16.3	16.0
	(4.7)	(4.7)	(4.7)	(4.6)	(4.5)	(4.7)	(4.6)	(4.2)
Precipitation [mm]	335	292	340	359	321	293	323	339
	(245)	(236)	(245)	(251)	(232)	(226)	(234)	(223)
N. of relatively hot days	3.9	3.8	3.9	3.8	3.9	4.3	4.0	3.5
	(4.3)	(4.2)	(4.3)	(4.3)	(4.3)	(4.6)	(4.4)	(3.9)
N. of relatively heavy rains	3.6	3.7	3.5	3.6	3.6	3.6	3.5	3.6
	(2.4)	(2.5)	(2.4)	(2.3)	(2.3)	(2.7)	(2.3)	(2.1)
Per capita expenditure [$]	1455	656	1135	3634	2206	927	1776	6357
	(1373)	(378)	(604)	(2872)	(2177)	(577)	(920)	(4885)
Per capita income [$]	1384	835	1233	2508	2189	1243	1965	4649
	(1409)	(661)	(995)	(2920)	(2385)	(1057)	(2442)	(5189)
Percent agricultural laborers [%]	8.8	6.6	10.1	5.6	6.1	5.5	6.6	4.1
	(28.3)	(24.8)	(30.2)	(22.9)	(24.0)	(22.9)	(24.8)	(19.8)
Percent agricultural self-employed [%]	19.1	6.8	20.0	27.5	2.1	1.7	2.3	2.3
	(39.3)	(25.1)	(40.0)	(44.6)	(14.3)	(12.9)	(14.9)	(15.0)
Observations	338,669	34,029	34,237	32,440	323,774	40,667	33,054	24,200

Notes: Table shows summary statistics of the main variables we use in this research from 1998 to 2018. Standard deviations are in parentheses below the numbers. Panels A and B show the values for rural and urban households, respectively. Columns (2-4) are for subsamples of rural households in 1th, 5th and 10th expenditure deciles, respectively. Columns (6-8) are similar to columns (2-4) but for urban households. Income and expenditure data is in 2016 USD (USD 1 = IRR 36,440). We define agricultural laborers as households whose agricultural wage is more than half of household's total income. Definition of agricultural self-employed is similar.

Table 3 shows within and between district variation of weather variables in panel A. The bulk of variation in precipitation and temperature is between variation. However, these variables have enough within variation, too. Since, we defined extremes on a relative basis, the main part of variation is within variation for these variables. Our identification strategy mostly relies on within district variation of the variables. For expenditure and income variables reported in panel B within variation is greater than between variation.

Table 3: Within and between variation of variables

VARIABLES	(1)	Mean (2)	Std. Dev. (3)	Min (4)	Max (5)	Observations (6)
Panel A: Weather						
Temperature [C]	overall	17.5	4.6	6.2	28.8	N = 5943
	between		4.6	7.3	28.1	n = 283
	within		0.6	14.4	19.8	T = 21
Precipitation [mm]	overall	361.1	315.3	0	2516.1	N = 5943
	between		300.1	40.9	1771.5	n = 283
	within		98.4	-147.8	1179.5	T = 21
N of Rel. Hot Days	overall	3.8	4.4	0	34	N = 5943
	between		0.2	3.1	4.4	n = 283
	within		4.4	-0.5	33.9	T = 21
N. of Rel. Heavy Rains	overall	3.7	1.8	0	16	N = 5943
	between		0.1	3.3	4.1	n = 283
	within		1.8	-0.4	16	T = 21
Panel B: HEIS						
Rural Expenditure [$]	overall	1,654	629	295	16,446	N = 5292
	between		407	668	3,591	n = 253
	within		480	-482	14,509	T = 21
Rural Income [$]	overall	1,451	598	-1,486	7,216	N = 5292
	between		408	616	2,968	n = 253
	within		438	-1,444	6,163	T = 21
Urban Expenditure [$]	overall	2,257	815	154	11,560	N = 5230
	between		465	950	4,854	n = 254
	within		670	-290	10,280	T = 21
Urban Income [$]	overall	2,170	859	330	24,985	N = 5230
	between		473	976	4,720	n = 254
	within		718	-448	23,559	T = 21

Notes: Table shows within and between variation of our main weather and HEIS variables in panels A and B, respectively. Data used in this tables is in district-year level. We use weighted average of real per capita income and expenditure for urban and rural areas to generate district-year level data in panel B.

3 Empirical Strategy

We employ a district fixed effect estimation strategy similar to Auffhammer et al. (2006) and Deschênes and Greenstone (2007). Our main specification is as follows:

$$Y_{idt} = W_{dt}\beta + X_{idt}\gamma + \alpha_d + \lambda_d^1 t + \lambda_d^2 t^2 + \epsilon_{idt} \tag{1}$$

Y_{idt} is the dependent variable for household i residing in district d during year t. For our main results, the dependent variable is the natural logarithm of real annual per capita household expenditure. W_{dt} is the vector of four weather variables (average annual temperature, annual precipitation, the number of relatively hot days and the number days with relatively heavy rain) measured in district d during year t. X_{idt} is a vector of household specific controls including percent literate, percent male, average age, and household size. α_d represents district fixed effects and $\lambda_d^1 t + \lambda_d^2 t^2$ are controlling for district-specific quadratic time trends. ϵ_{idt} is the idiosyncratic error term. We correct the standard errors to allow for district-level clustering. All results are weighted to represent population averages.

The inclusion of district fixed effects controls for any time-invariant district characteristics that matter for outcomes. In other words, estimation of weather impacts relies on the within district correlation of outcomes with temperature and precipitation. Therefore, omitted variables like soil quality, elevation, and land slope that cause a bias in cross-sectional studies are taken care of. For example, districts in the south east of Iran (Sistan and Baluchistan province) have relatively low per capita expenditure and a very hot and dry climate, while the districts in northern provinces like Mazandaran and Gilan have relatively high expenditure per capita and a mild and wet climate. If we don't include district fixed effects, we will overestimate the impact of weather on household expenditure. Furthermore, while overall climatic condition of a district is predictable and might be correlated with unobservable variables, year-by-year variations in temperature and rainfall are plausibly random variation making the identification strategy more appealing.

In addition to fixed district characteristics, time varying factors might be correlated with

climate trends. For example, a gradual increase in temperatures (global / local warming) might be confounded with gradually improving agricultural productivity due to expansion of high yield varieties. On the other hand, depletion of aquifers or soil erosion might cause a decline in livelihoods which can be confounded with climate shocks. To control for such factors, we include district specific quadratic time trends. These controls allow for a heterogeneous trend in per capita expenditures across districts up to the second order.

While inclusion of district specific time trends is common in the literature (e.g., Lobell et al. (2011) for California State; Narloch (2016) for Vietnam; and Flatø et al. (2017) for South Africa), another approach is to include year fixed effects (e.g. Deschênes and Greenstone (2007) for the United States; Burgess et al. (2017) for the United States and India; and Dell et al. (2012) for a World Sample). The former strategy allows for complete heterogeneity across districts but restrict the functional form of the time trend (e.g. to a second order polynomial). However, the latter approach does not impose a specific functional form on the trend but restrict the time effects to be identical across districts. While we present robustness checks with year fixed effects, we prefer to use district specific quadratic time trends for two reasons.

First, year fixed effects remove part of the weather variation that is common to all regions in a year. For vast areas like the United States, India, or the world this is not a serious concern since the remaining weather variation is enough for identification. But in samples covering not as large areas inclusion of year fixed effects could remove the bulk of weather variation that is common to most regions. Iran (similar to the state of California, Vietnam, and South Africa in Lobell et al. (2011), Narloch (2016) and Flatø et al. (2017)) is not a small country but most parts of the country experience similar weather shocks. Figure 5 shows temperature deviations for each district from its own 21-year average for each year. A visible pattern is that deviations tend to move together. In other words, within district year-on-year temperature changes are similar across districts. Therefore, inclusion of a completely global time trend (year fixed effects) would remove this variation and leave no statistical power to identify our effect of interest. Instead, inclusion of district specific quadratic trends allows for

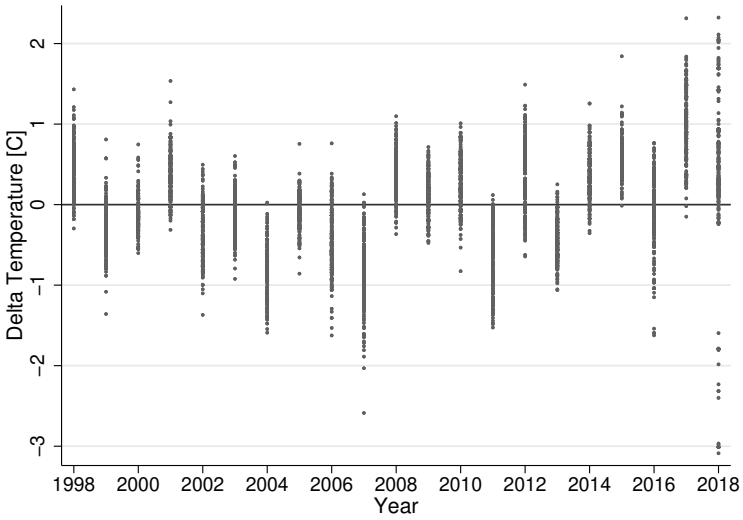


Figure 5: Difference of annual temperature from district average

Notes: Figure shows difference of annual temperature from district average. Each dot stands for a district in a year.

heterogeneity in the time path of districts but does not remove common shocks (whatever is left after removal of quadratic trends) leaving more variation to identify weather impacts.

Second, it is well known that fixed effects estimators are sensitive to measurement error. This is because they rely on deviations from means of variables and hence retain more of measurement error and the signal to noise ratio deteriorates. This issue could result in attenuation bias (Fisher et al. 2012). We do not have weather stations in all districts of Iran and the distance between two stations is often quite large. This is a source of measurement error that might not be an issue in developed countries with denser weather station networks (Auffhammer 2018). The specification with year fixed effects has more fixed effects and then would strengthen the attenuation bias.

A related concern is the addition of new weather stations during the study period. Figure A.1 in Appendix shows the number of IMO stations during 1959 to 2018. Number of stations is increasing over time from about 30 stations in 1959 to more than 450 stations in 2018. Station opening is not random because developed and populous areas are more likely to receive stations earlier. To avoid the potential sample selection from new stations, in a robustness

test we only use 160 stations that opened before 1998[8] (Columns (5,6) in Table 5).

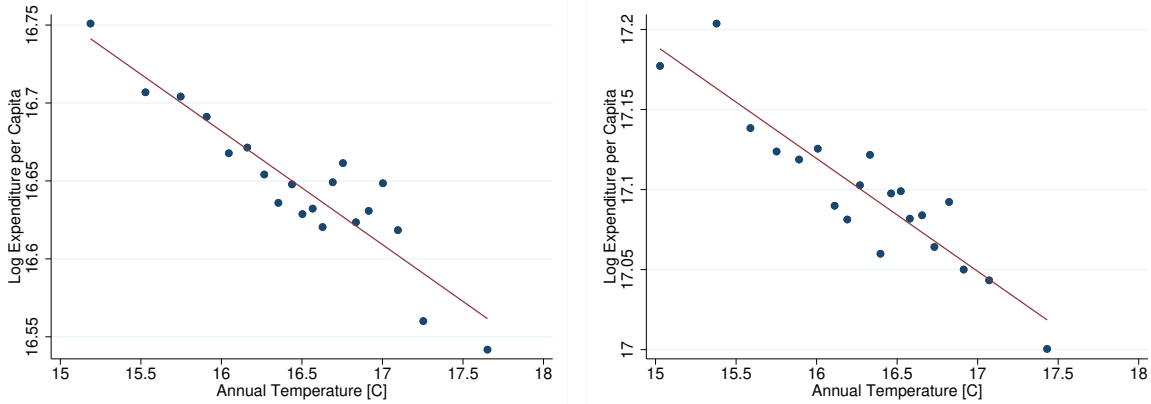
A well-known limitation of the panel data approach is that it captures short-term impact of weather fluctuations, but not the long-term effects of climate change. Adaptation strategies in the short and long-run differ and what matters for investigation of climate change effects is the long-run effects. For example, in response to a dry year farmers might use less of other complementary inputs such as fertilizer to reduce costs. But when the climate changes farmers might invest in irrigation infrastructure to compensate for loss of rainfall. It seems agents have more adaptation choices in the long-run and thus fixed effects estimates overstate the true impact of climate change. For example, farmers might change crops or plantation time to combat climate change. But some short-term adaptation strategies like rely on groundwater may not be sustainable in the long-run, resulting in larger long-term effects (Burke and Emerick 2016). Hence the bias may work in either direction depending on the nature of the adaptation options available to economic agents (Auffhammer 2018). However, Burke and Emerick (2016) show longer-run adaptation appear to have mitigated a limited fraction of the large negative short-run impacts.

To investigate the heterogeneities across expenditure deciles (distributional effects), we use a similar strategy to average effect estimation (equation(2)).

$$Y_{idt} = \sum_j (J_{ij} \times W_{dt}\beta_j) + X_{idt}\gamma + \alpha_d + \lambda_d^1 t + \lambda_d^2 t^2 + \epsilon_{idt} \tag{2}$$

Where J_{ij} is an indicator variable that equals 1 if expenditure decile of household i equals to j and is 0 otherwise. Then β_j will be the vector of coefficients of weather variables for expenditure decile j. In a similar way, we estimate the heterogeneities across quartiles of average district temperature.

[8]The result is the same as keeping the stations that provide daily measurements for more than 95% of the days from 1998 to 2018.



(a) Rural

(b) Urban

Figure 6: Bin scatter of log annual expenditure per capita and annual temperature

Notes: Figure shows bin-scatter plots of log per capita expenditure of rural (panel A) or urban (panel B) households and annual temperature. District fixed effects and a linear time trend are controlled, too.

4 Results: average effects

In this section we present estimation results in four sub-sections. First, we present the main results for various dependent variables. Here we split the sample to rural and urban households because we believe different mechanisms might be operative in the two areas. Second, we conduct several robustness checks to test the sensitivity of the results. Third, we look at a range of expenditure and income categories to shed light on potential mechanisms. Finally, we look at the heterogeneity of impacts across various groups.

4.1 Baseline estimates

Figure 6 shows a visual representation of our average effects by plotting bins of log annual per capita expenditure versus bins of average annual temperature while controlling for district-level fixed effects and a global time trend. Consistent with the previous literature, we find a negative partial correlation between annual temperature and per capita expenditure. The relation is similar across urban and rural areas.

Table 4 shows the average effect of temperature and rainfall on household per capita expenditure. Panels A and B respectively show results for rural and urban households. In columns

Table 4: Impact of weather variation on annual expenditure per capita of households

	Pooled OLS		Fixed Effect		
VARIABLES	(1)	(2)	(3)	(4)	(5)
Panel A: Rural					
Temperature [°C]	-0.0181***	-0.0123***	-0.0826***	-0.0896***	-0.0805***
	(0.00462)	(0.00376)	(0.00737)	(0.00590)	(0.00612)
Precipitation [100 mm]	0.0288***	0.0216***	0.00761**	0.0114***	0.0148***
	(0.00531)	(0.00437)	(0.00360)	(0.00352)	(0.00478)
N. of Rel. Hot Days					-0.00442***
					(0.00107)
N. of Rel. Heavy Rains					-0.00378
					(0.00250)
Observations	338,669	338,669	338,669	338,669	338,669
Adjusted R-squared	0.035	0.161	0.244	0.262	0.262
Panel B: Urban					
Temperature [°C]	-0.0155**	-0.00621	-0.0547***	-0.0506***	-0.0473***
	(0.00744)	(0.00549)	(0.00557)	(0.00657)	(0.00517)
Precipitation [100 mm]	0.0157**	0.0105*	0.00868**	0.0102***	0.00932*
	(0.00668)	(0.00558)	(0.00420)	(0.00329)	(0.00530)
N. of Rel. Hot Days					-0.00173
					(0.00150)
N. of Rel. Heavy Rains					-0.000212
					(0.00217)
Observations	323,774	323,774	323,774	323,774	323,774
Adjusted R-squared	0.011	0.279	0.379	0.386	0.386
Controls	N	Y	Y	Y	Y
District FE	N	N	Y	Y	Y
District Quad. Trend	N	N	N	Y	Y

Notes: Panels A and B show the regression results for rural and urban subsamples, respectively. Dependent variable in all columns is log real annual expenditure per capita. Columns (1) doesn't have any control variables or fixed effects. In column (2), we include household specific control variables (percent literate, percent male, household size and average age) and a linear time trend. In columns (3-6) district fixed effects are included. In column (3) a general time trend (year) is controlled but in columns (4,5) district specific quadratic time trends are included. We include year fixed effect in column (6) instead of district specific time trend. All standard errors are corrected for district-level clustering and are reported in parenthesis below the coefficients. *** p<0.01, ** p<0.05, * p<0.1

(1) and (2) we show results of an OLS regression with and without controls respectively. Our main estimation strategy is presented in columns (3) to (5) where we include household controls and district fixed effects. The coefficient of temperature is robust across these three columns. Column (5) shows our preferred specification with district specific quadratic time trends and measures of extreme weather events. We observe that a 1 degree increase in temperature results in 8.1 and 4.7 percent reduction in expenditures respectively for rural and urban households. Both coefficients are highly significant. A smaller temperature effect for urban areas is consistent with lower vulnerability of urban livelihoods. The impact of rainfall is smaller and less significant than temperature. A 100 mm increase in rainfall results in 1.5 and 0.9 percent increase in expenditures respectively for rural and urban areas. Among variables capturing extreme weather events, only the extremely hot days in rural areas has a significant effect.

4.2 Robustness Checks

We conduct five robustness checks to assess the sensitivity of the average effects. Table 5 and Figure 7 shows the results of these robustness checks. First, the HEIS sample is small in some districts which might cause sensitivity to measurement error. In column (1) of Table 5 we keep districts that have a minimum of 30 households in each of rural and urban areas for each year. This restriction removes 7 and 13 percent of the rural and urban samples respectively but the estimated coefficients and their significance are unchanged. Only the precipitation coefficient for the urban sample becomes insignificant.

Second, weather variables are defined at district-year level, but we use household-level data in our regressions. To check whether having a group of households within a district is causing significant results, we collapse the data to district-year observations using sampling weights. We use the log of weighted average annual per capita expenditure as our dependent variable. The estimated results in column (3) are even stronger than our household-level regressions. Here, the standard errors are corrected for district-level clustering and other controls are included as in our preferred specification.

Table 5: Robustness checks

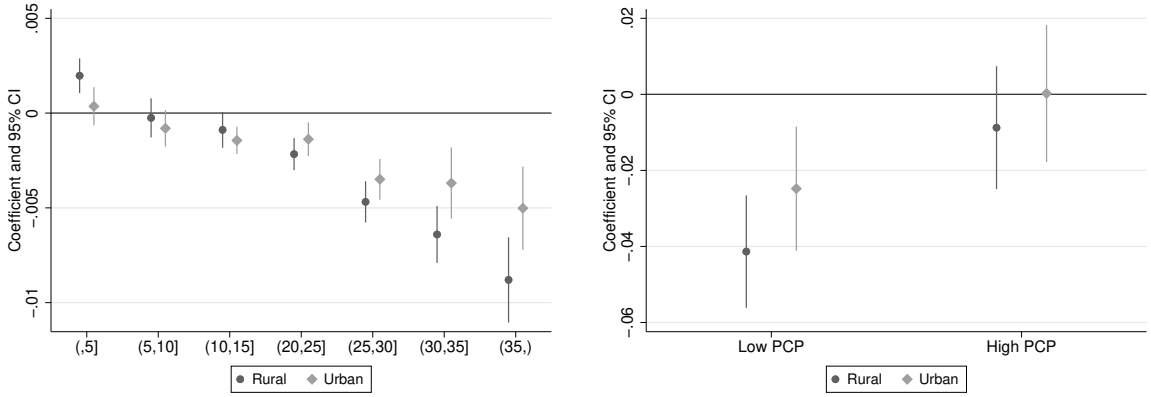
VARIABLES	HEIS≥ 30 (1)	Collapsed (2)	Station (3)	Station Miss (4)	Cubic (5)	Year FE (6)
Panel A: Rural						
Temperature [C]	-0.0822***	-0.0813***	-0.0627***	-0.0709***	-0.0272***	-0.00643
	(0.00657)	(0.00731)	(0.00587)	(0.00831)	(0.00537)	(0.0121)
Precipitation [100 mm]	0.0140***	0.00920**	0.0194***	0.0142**	0.0153***	0.000541
	(0.00509)	(0.00461)	(0.00478)	(0.00602)	(0.00400)	(0.00507)
N. of Rel. Hot Days	-0.00431***	-0.00422***	-0.00481***	-0.00525***	0.000967	0.000323
	(0.00113)	(0.00134)	(0.000983)	(0.00133)	(0.00119)	(0.00140)
N. of Rel. Heavy Rains	-0.00366	-0.000795	-0.00504	-0.00407	-0.00242	-0.00321
	(0.00265)	(0.00240)	(0.00333)	(0.00393)	(0.00230)	(0.00267)
Observations	315,180	5,292	353,544	215,053	338,669	338,669
Adjusted R-squared	0.268	0.570	0.261	0.265	0.284	0.269
Panel B: Urban						
Temperature [C]	-0.0526***	-0.0652***	-0.0381***	-0.0367***	-0.0142***	-0.0241*
	(0.00593)	(0.00818)	(0.00393)	(0.00462)	(0.00444)	(0.0131)
Precipitation [100 mm]	0.00832	0.00944*	0.0153***	0.0140**	0.00914*	0.00120
	(0.00600)	(0.00500)	(0.00487)	(0.00600)	(0.00493)	(0.00597)
N. of Rel. Hot Days	-0.00114	-0.00211*	-0.00265**	-0.00273*	0.000793	-0.00293**
	(0.00173)	(0.00122)	(0.00132)	(0.00163)	(0.00109)	(0.00114)
N. of Rel. Heavy Rains	0.000289	0.00191	-0.00242	-0.00274	-6.93e-07	-0.00375**
	(0.00238)	(0.00256)	(0.00221)	(0.00242)	(0.00221)	(0.00175)
Observations	280,521	5,230	332,950	248,438	323,774	323,774
Adjusted R-squared	0.396	0.513	0.384	0.401	0.397	0.394

Notes: See notes on Table 4. In column (1) we only keep districts in HEIS data which have at least 30 observations in each urban and rural areas in each year. In column (2) we collapse the data to district-year level and estimate a similar equation to column (5) in Table 4. In column (3) and (4) we use station level weather data and generate district level weather data by using the average of all stations inside the borders of the district. Here we use only stations established up until to 1998. We replace province level data for missing district level data in column (3) but drop these districts in column (4). In column (5) we replace the district specific quadratic time trend in our main specification (column (5) in Table 4) with a cubic district specific time trend. And finally in column (6), we use year fixed effect instead of district specific time trends.

The third robustness check deal with non-uniform addition of weather stations. In columns (3,4) we keep the stations established up until 1998. In these two columns, we use station-level weather data and create district-level weather variables by averaging readings of stations inside the borders of a district[9]. In column (3) we use province averages for districts without any weather stations but in column (4) we drop these districts. The temperature effects are slightly smaller for rural and urban areas, but the rainfall effects are the same.

Fourth, we try to control for time trends more flexibly. First by adding district-specific

[9]Our main weather data is provided by NDWMC at district-level which uses meteorological interpolation methods to compute gridded temperature data from terrestrial measurements correcting for elevation.



(a) Temperature Bins

(b) Precipitation Level

Figure 7: Results for a different definition of weather variables

Notes: Figure shows the coefficients of regressing household expenditure on weather. Dependent variable is log real annual expenditure per capita. Panels A and B show coefficients and 95% confidence intervals of temperature and precipitation variables, respectively. In panel A, we use number of days in a year for a district that temperature is inside each of the bins. Bin (15,20) is omitted as a reference. In panel B, we define low and high precipitation as dummy variables which equal to 1 if a the annual precipitation in that year is in first and third tercile of historical annual precipitation for that district, respectively. The second tercile (moderate precipitation) is omitted as a reference. District fixed effect, district specific quadratic trend and household specific control variables (percent literate, percent male, family size and average age) are included in the regression, too.

cubic trends in column (5) of Table 5. Then by replacing district-specific polynomial trends with global year fixed effects in column (6). These additional checks are very demanding and reduce the coefficient estimates of weather variables significantly. Yet, the adjusted R^2 does not change much meaning that the explanatory power of the model is not improved. Therefore, we prefer the model with quadratic trends but admit that there is a high correlation between district-specific cubic trends and within district weather variation.

Finally, we examine the sensitivity of results to assuming a linear functional form for weather variables. Instead of using yearly temperature and precipitation, we use a flexibly defined set of temperature variables similar to Burgess et al. (2017). We divide the entire temperature interval into 8 bins[10] and generate 8 variables showing the number of days within each bin in a year[11]. In addition, similar to Burgess et al. (2017), we divide annual pre-

[10]The intervals are $(-\infty,5]$, (5,10], (10,15], (15,20], (20,25], (25,30], (30,35], $(35,\infty)$.

[11]The sum of these 8 variables will be 365 days. Therefore, we include 7 variables and measure the impact of a day in given bin relative to the $(15, 20]$ temperature interval.

cipitation into three groups of low, moderate and high precipitation using historical annual precipitation records for each district[12]. Figure 7 shows the results of including these variables in our preferred specification excluding extreme weather variables. Interestingly, temperature impact on rural and urban households seems to be close to linear.

5 Results: distributional effects

So far we have established a robust relation between temperature and household expenditures in rural and urban areas. However, households might receive heterogeneous effects due to different levels of exposure to climate shocks and vulnerability. An important determinant of vulnerability is households resources. The level of household expenditure is an indicator of such resources. Therefore, we categorize households into deciles of per capita expenditure and estimate the temperature effects for each decile in the next subsection. We establish that poor deciles receive a much greater impact from temperature increases compared to richer deciles confirming our priors that lack of resources is detrimental to household's adaptation capacity. Then we dig deeper and try to see whether we can decompose the greater impact on poorer households to components of exposure and vulnerability by looking at the heterogeneity across income sources and geographical regions.

5.1 Temperature effects for deciles

Figure 8 shows the estimated coefficients and 95 percent confidence intervals for deciles across rural and urban samples. There are three interesting patterns in these results. First, for the poorest rural decile a one degree increase in temperature results in 15 percent reduction in per capita expenditure. This is 1.8 times greater than the estimated average effect. Similarly, the estimated coefficient for the poorest urban decile is 11 percent which is more than double the corresponding average effect. Second, the magnitude of the temperature effect sharply declines and the richest deciles virtually receives no significant impact from increases in temperature. Third, for all deciles the impact is greater for rural households compared to urban ones. The

[12]Moderate precipitation is dropped as the reference category.

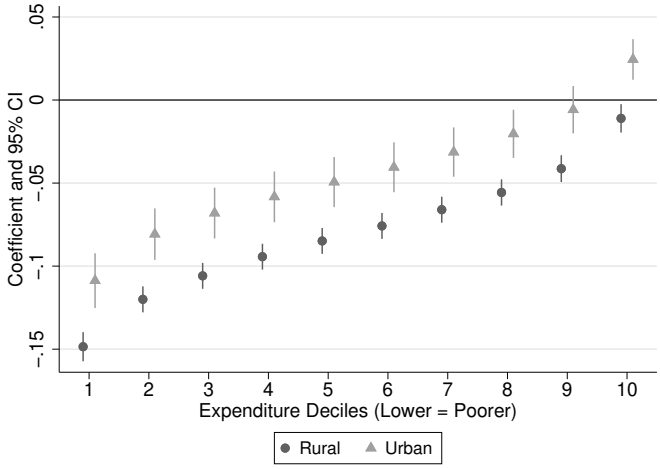


Figure 8: Heterogeneity of temperature variation impact across expenditure deciles

greater impact on the poor corroborates previous findings in the literature (e.g. Dell et al. 2012). However the evidence is more clear in our study.

5.2 Exposure versus vulnerability

The greater impact of temperature shocks on poorer households could be either due to greater exposure or higher vulnerability. Households working in climate sensitive activities and those living in unfavorable climatic conditions have higher exposure. If the share of poor households is disproportionately higher in areas with greater exposure, then the greater temperature impact on them is simply reflecting higher exposure. The relevant policy response here would be to reduce exposure by replacing climate sensitive livelihoods. However, if the poor and the rich have similar exposure to climatic shocks, then individual vulnerability matters. In this case compensatory policies should try to improve household endowments and combating poverty is the avenue to fight climate change effects. In what follows, we focus on the rural sample. The pattern of results are similar for the urban sample and we avoid presenting them for brevity.

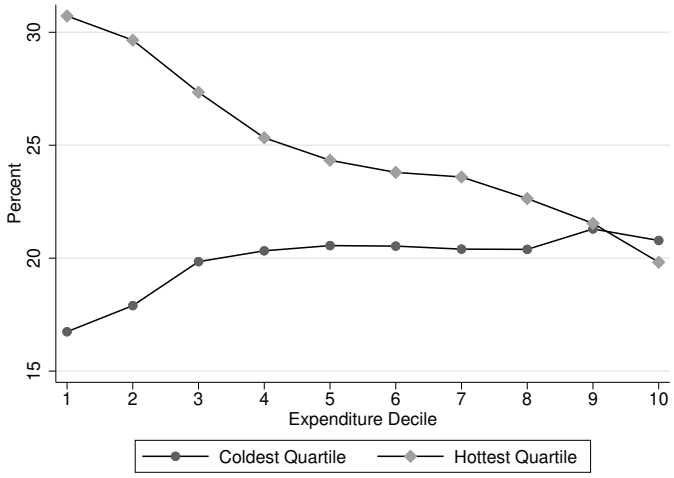
We look into two patterns to see the relevance of each of above stories in our case. First, we split districts into quartiles based on average long run temperature (21 years) and esti-

mate the results for these sub-samples. Hot districts have higher exposure because temperature increases in already hot areas might cause greater damages. In contrast, households in historically warmer districts might have devised better coping strategies to combat heat. For example, they might cultivate heat-resistant varieties and have air conditioning devices. Therefore, it is theoretically ambiguous which mechanism dominates.

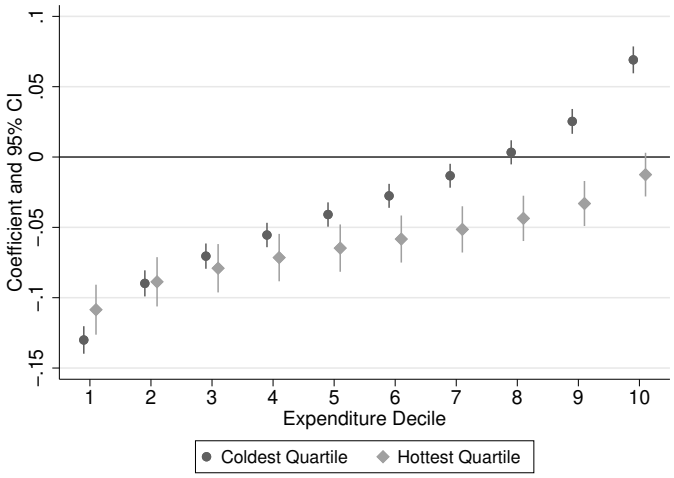
Figure 9-(a) shows that a higher percentage of the poor deciles live in the hottest quartile. This is evidence that poorer households might have greater exposure to extreme heat. Looking at the temperature impact on household expenditure across the coldest and hottest quartiles in Figure 9-(b) we see that bottom 4 deciles receive a similar impact. This suggests that for the poorest deciles the vulnerability story matters the most. Living in cold or hot regions does not matter, and upon receiving a temperature shock poor households across regions receive a similar impact. Households above the median of expenditure distribution receive a widely different impact across the coldest and hottest quartiles. While the three top deciles of households in the coldest quartile receive no or a positive impact, these deciles receive a negative effect in the hottest quartile.

The second pattern we consider here is the heterogeneity of temperature impact across agricultural and non-agricultural households. Agricultural and non-agricultural households might have different exposure and vulnerability. Temperature increases and precipitation decreases adversely affect agricultural production. Lower food availability and higher prices negatively affects non-farmers. But farmers receive two opposing effects: a decline in output and a rise in prices. We categorize households into three groups based on the share of various sources in their total income. Agricultural laborers are those that receive at least half of their income from wage agriculture. Agricultural self-employed households are those with at least half of income from agricultural businesses they operate. Finally, non-agricultural earners are those with at least half of income coming from non-agricultural activities. We define a fourth group of agricultural earners as those with at least half of income from the sum of agricultural labor and self-employment. This last group is the complement of non-agricultural earners.

Figure 10-(a) looks at the share of agricultural earners across deciles. Apart from the first



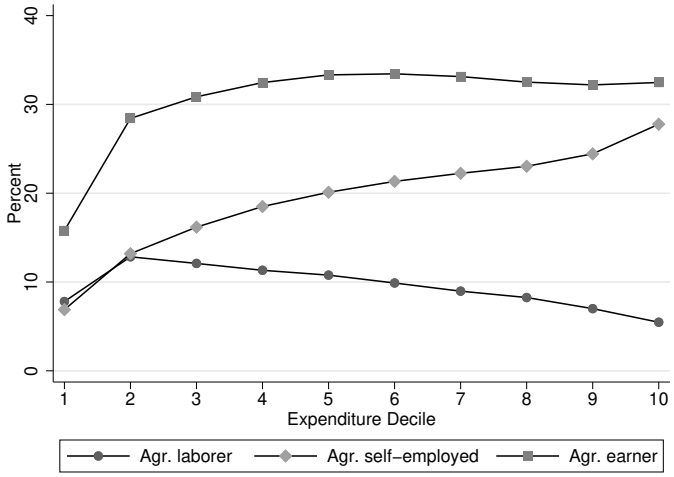
(a) Percentage of households living in hot and cold regions



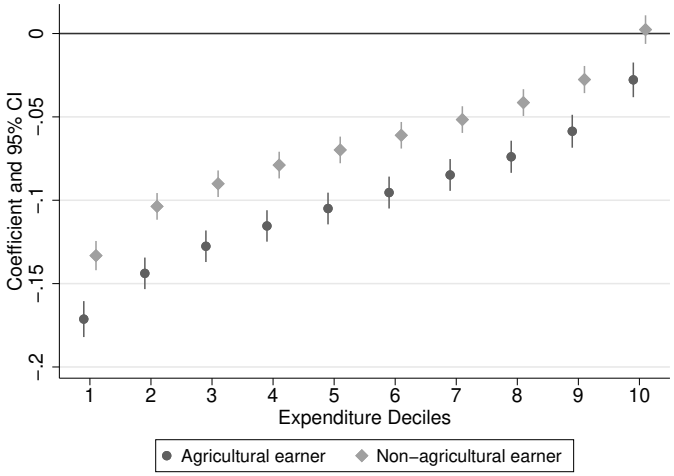
(b) Temperature effects across hot and cold regions

Figure 9: Heterogeneity of expenditure deciles across hot and cold regions

Notes: Panel (a) shows percent of people in each expenditure decile living in coldest and hottest quartiles. Panel (b) shows coefficients and 95% confidence intervals of interaction of mean temperature quartile and annual temperature. Annual precipitation, N. of relatively hot days and N. of relatively heavy rains as well as district fixed effects, district specific quadratic time trends and household specific characters are included in the regressions. Numbers 1 to 4 in labels are sorted for coldest to hottest quartiles.



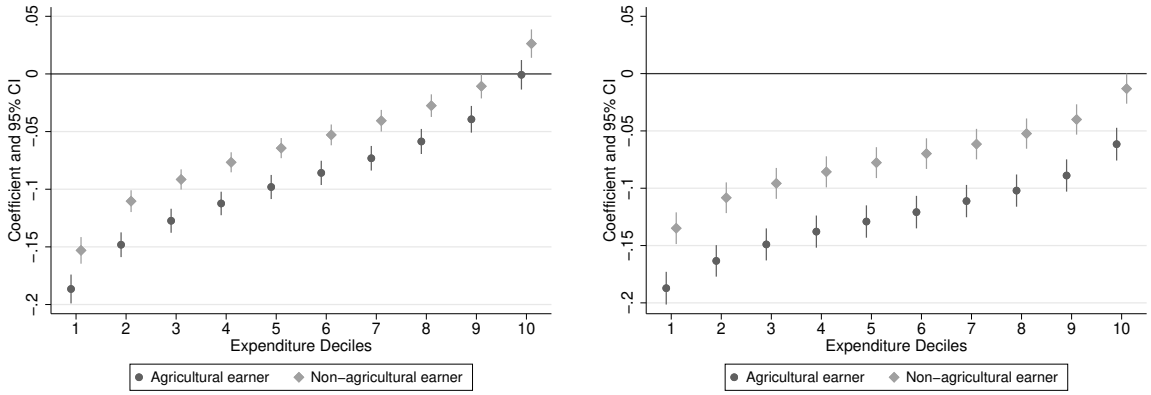
(a) Percentage of households with various agricultural income sources



(b) Temperature effects across agricultural and non-agricultural households

Figure 10: Heterogeneity of expenditure deciles across agricultural and non-agricultural households

Notes: Here we define agricultural laborers and agricultural self-employed and agricultural earners as households whose agricultural wage income, agricultural self-employed business income, and total agricultural income are more than half of household total income, respectively. Panel (a) shows percent of people in each expenditure decile that are in each of the groups. Panel (b) shows coefficient and 95% confidence intervals for subsamples of agricultural earners and non-agricultural earners.



(a) Coldest quartile

(b) Hottest quartile

Figure 11: Difference of farmers and non-farmers in cold and hot regions

Notes: See notes on Figure 10. Here we repeat the estimates of panel a of Figure 10 but for subsamples of districts in coldest and hottest quartile.

decile, the share of agricultural laborers declines as move up the expenditure distribution. In contrast the share of agricultural self-employed households increases. This means that apart from the first decile, the share of agricultural earners remains constant over deciles. Figure 10-(b) shows the temperature effect across deciles for agricultural and non-agricultural earners. Greater exposure to climate shocks in agriculture is reflected in the gap between the two groups in this figure. Agricultural earners always receive a larger detrimental impact from temperature increases compared to non-agricultural earners. However, as we move up the expenditure distribution to richer households the adverse impact declines for both groups of households.

Figures 11 combines the two patterns discussed above. In Figure 11-(a) we look within the coldest quartile of districts and separate the impact for agricultural and non-agricultural households across deciles. Figure 11-(b) presents similar estimates for the hottest districts. Three points are worth emphasizing. First, agricultural earners receive a greater impact across deciles relative to non-agricultural earners in both regions. Second, the gap between agricultural and non-agricultural households is larger in the hottest quartile. Third, the most significant change is across deciles. In other words, it seems that individual vulnerabilities play

a significant role. Households in the poorest decile receive the greatest impact after controlling for exposure (type of activity and geography). Moving across deciles the temperature effect is reduced rapidly.

6 Discussion and Conclusion

In this paper, we use 21 years of household-level data from a middle-income country, Iran to study the distributional impact of climate change. Our preferred estimates show that a one Celsius degree increase in annual temperature leads to 8.1 percent decrease in per capita expenditure for rural households. Also, a 100 mm increase in annual precipitation results in 1.5 percent increase in per capita expenditure for rural households. We also find a significant impact for extremely hot days in rural areas even after linearly controlling for temperature and rainfall. The magnitude of the temperature effect in our study is larger than panel studies (such as Dell et al. (2012) with a 1.5 percent negative effect) but it is similar to cross-sectional studies (for example, Dell et al. (2009) with a 8.5 percent negative effect). Also, the literature finds a significant precipitation effect only in Africa with less clear effects elsewhere (Dell et al. 2014), but our results clearly demonstrate a negative effect of dry years. The fact that our average estimates are larger than previous country-level panel studies could be due to the use of district-level data that matches outcomes and weather variables more precisely. Another reason for the large estimates could be the separation between urban and rural households which is impossible in aggregate-level studies.

Our distributional results confirm the nascent literature that looks at the heterogeneity of climate impact across poor and rich countries and households (e.g., Kalkuhl and Wenz 2020; Dell et al. 2012; Hsiang and Meng 2015; Hertel et al. 2010; Jacoby et al. 2011). We find a much stronger impact of temperature variation on the poor deciles in rural and urban areas. The higher impacts on poor households could be due to greater exposure or higher vulnerability. In order to disentangle these two explanations we split the sample along geographical and occupational lines. We find that the hottest quartile of districts receive a greater impact from temperature increases than the coldest quartile. But this gap is virtually non-existent

for the poor deciles. This pattern shows that the role of individual vulnerabilities is more important than exposure. To complement this, we also look at the gap in temperature impact for agricultural and non-agricultural earners. Here, agricultural households always receive a greater impact across deciles. But the gap between the two groups is much smaller than the reduction we observe as households get richer. This pattern again emphasizes the role of individual vulnerabilities but gives some role for higher exposure and sensitivity of certain activities (e.g. agriculture) to climate change.

The takeaway messages from our paper are two folds. First, distributional impacts of climate change dwarf the average effects. The poorest decile receives twice the impact of the richest one in our study. Second, it seems that individual vulnerabilities are more important in explaining the differences in temperature impact. Differences in exposure and sensitivity play some role but what matters in the end is whether the household has enough financial resources to combat the adverse effects of increased temperatures.

Our study has at least three limitations. First, we are unable to empirically test the mechanisms of weather impact on income per capita directly. For example, we don't observe district-level crop prices to investigate the weather impact on prices directly. Our result that agricultural earners receive a greater impact indirectly shows that the loss of produce dominates the increase in prices for poor households. But the two effects cancel out for rich households. Similarly, we don't have access to health, mortality, crime, and labor supply data to test the indirect impact of weather on household expenditure. Second, by using the panel data approach and year-on-year weather variations, we are able to deal with the endogeneity problem, but this approach only considers short run adaptations and not long run strategies (Auffhammer 2018). Generally, agents have more adaptation choices in the long run, for example, farmers in the long run can switch crops, or migrate to less affected areas which would dampen the estimated impacts of climate change. However, there are also examples of adaptation options that are available in the short run and not in the long run. One example is availability of limited groundwater resources that allow short run smoothing of rainfall shocks. But due to reservoir depletion this strategy is not available in the long run. Hence

the bias may work in either direction depending on the nature of available adaptation options. Finally, we are unable to include a fully flexible time trend due to high spatial correlation of weather shocks across districts. We control for district-specific quadratic time trends to allow for potential time-dependent confounders. But this strategy is not fully flexible and there might be remaining confounders.

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A Appendix

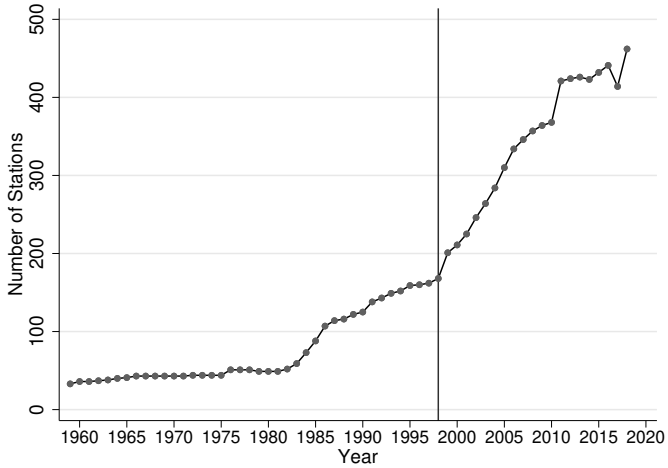

Figure A.1: Number of weather monitors during the time

Notes: Figure shows number of weather monitors in our weather data provided by IMO during 1960 to 2018. The vertical line in year 1998 is inserted to show the first year in this research. In this year there are about 160 monitors.

Table A.1: Average effects of global warming on pure urban centers

VARIABLES	Agr < 20 (1)	Agr < 10 (2)	Agr < 5 (3)	Big cities (4)
Temperature [°C]	-0.0479***	-0.0402***	-0.0412***	-0.0312**
	(0.00570)	(0.00643)	(0.00804)	(0.00929)
Observations	272,914	177,282	116,851	59,709
Adjusted R-squared	0.391	0.402	0.423	0.379

Notes: See notes on Table 4. In columns (1-3), we keep urban centers with agricultural workers less than 20, 10, and 5 percent of agricultural workers in first 3 years of our data (1998-2000). In column (4), we keep observations of 7 big cities which are Tehran, Mashhad, Isfahan, Tabriz, Shiraz, Ahvaz, and Karaj.