yönetim ve ekonomi araştırmaları dergisi
journal of management and economics research
Cilt/Volume: 22 Sayı/Issue: 3 Eylül/September 2024 ss. /pp. 104-130
M.A. Soytaş, D. Durak Uşar, http://dx.doi.org/10.11611/yead.1423671

AŞIRI HAVA KOŞULLARI VE TALEP: TÜRKİYE KLİMA PAZARI ÜZERİNE AMPİRİK BİR ÇALIŞMA

Mehmet Ali SOYTAŞ [*]

Asst. Prof. Damla DURAK UŞAR (Ph.D.) [**]

ÖZ

Aşırı hava koşulları hem işletmeleri hem de tüketicileri önemli şekillerde etkileyebilir. Firmalar, üretim ve operasyonlardaki değişiklik ve kesintilerden etkilenebileceği gibi, tüketicilerin çeşitli mal ve hizmetlere olan talebinin aşırı hava koşulları nedeniyle değişmesi nedeniyle talep tepkisinden de etkilenebilir. Bu çalışmada Türkiye klima pazarı için aşırı sıcaklıklar ile klima talebi arasındaki karşılıklı bağımlılığın varlığı araştırılmaktadır. Türkiye'de klimalara olan talep hem demografik faktörler hem de kişi başına düşen GSYİH' deki hızlı artış nedeniyle son yıllarda artmaktadır. Ancak, büyümenin hızı tekdüze olmayıp, Türkiye'nin farklı bölgelerindeki farklı iklim ve sosyoekonomik koşulların varlığı nedeniyle büyük farklılıklar göstermektedir. Şehir düzeyindeki iklimsel ve sosyoekonomik farklılıkların yanı sıra zaman ve kesitsel farklılıkları da hesaba katmak için, dinamik bir sabit etki (DFE) modeli tahmin edilmiş ve aşırı hava koşullarının klima talebi üzerindeki kısa ve uzun vadeli etkilerini belirlemek için eş bütünleşme çerçevesi kullanılmıştır. Aşırı sıcak hava nedeniyle tüketici talebinin önemli ölçüde arttığı uzun vadeli denge etkisine dair güçlü kanıtlar bulunmuştur.

Anahtar Kelimeler: *ARDL Modeli, Aşırı Hava Koşulları, Dinamik Panel Veri Analizi, Talep.*

JEL Kodları: *Q59, R11.*

EXTREME WEATHER AND DEMAND: AN EMPIRICAL STUDY ON THE TURKISH AIR CONDITIONER MARKET

ABSTRACT

Extreme weather conditions can impact both businesses and consumers in significant ways. Firms can be affected by changes and disruptions in production and operations but can also be affected through the demand response as consumer demand for different goods and services changes due to extreme weather. We investigate the interdependence between the extreme temperatures and the AC demand. Demand for ACs in Turkey has been growing in recent decades, driven by both demographic

[*] National Labor Observatory, Riyad/ Saudi Arabia, E-mail: msoytas@gmail.com.
[**] Turkish-German University, Faculty of Engineering, Industrial Engineering, İstanbul/ Türkiye, E-mail: damla.usar@tau.edu.tr.

Makale Geçmişi/Article History

Başvuru Tarihi / Date of Application	: 22 Ocak / January 2024
Düzeltme Tarihi / Revision Date	: 9 Temmuz / July 2024
Kabul Tarihi / Acceptance Date	: 18 Temmuz/ July 2024

Araştırma Makalesi/Research Article

factors and a period of rapid growth in GDP per capita. However, the pace of growth is not uniform and varies due to different climatic and socio-economic conditions in different regions of Turkey. To account for temporal and cross-sectional variation, as well as climatic and socio-economic differences at the city level, we estimate a dynamic fixed effects (DFE) model and use a co-integration framework to identify short- and long-run effects of extreme weather on AC demand. We find strong evidence of a long-run equilibrium effect where the consumer demand for ACs increases significantly due to extreme hot weather.

Keywords: *Auto Regressive Distributed Lag Model (ARDL), Demand, Dynamic Panel Estimation, Extreme Weather.*

JEL Codes: *Q59, R11.*

1.INTRODUCTION

According to the United Nations Office for Disaster Risk Reduction (UNDRR), the number of climate-related extreme weather events such as extreme temperatures, droughts, wildfires, storms and floods has increased significantly over the past 20 years (UNDRR, 2020). The 2003 European heat wave caused the death of more than 30,000 people, the destruction of forests, glaciers and water ecosystems, and a significant reduction in agricultural production. The total economic cost of the 2003 European heat wave is estimated at over €13 billion (United Nations Environment Programme, 2004). The 2019-2020 wildfires burned an estimated 170000 square kilometers of land, destroyed over 2000 buildings, killed at least 24 people and about one billion animals (Komesaroff and Kerridge, 2020). The bushfires were attributed to extreme fire weather and severe droughts caused by anthropocentric climate change, and were unprecedented in scale, duration, and economic loss (Lange and Gillespie, 2022). In 2022, monsoon rains caused devastating floods in Pakistan resulting in over 1,100 deaths, over 1,600 injured, 105,8000 houses destroyed or damaged, 735,000 livestock lost, and 2 million acres of crops affected (Government of Pakistan, National Disaster Management Authority, 2022). Researchers have documented that about 5 million people die each year from extreme cold or heat, accounting for 9.4% of annual global deaths (Zhao et al., 2021). These extreme weather events have a significant impact not only on natural ecosystems, but also on human social systems, especially the economy.

These examples highlight the urgency and importance of research into the impact of extreme weather conditions on production economics. The production economics literature has been concerned with the impact of extreme weather conditions on business operations and the economy. On the one hand, the literature addresses the impact of extreme weather and climate change and attempts to propose approaches to identify, assess, mitigate, and monitor the impact of climate change and extreme weather on the operational performance of production systems; on the other hand, it examines the behavioral dynamics of suppliers, employees, customers, and other stakeholders under extreme weather conditions. We are interested in buyers' behaviors and evaluate the impact of extreme weather on demand response.

Specifically, this work aims to provide new insights into the behavioral dynamics of buyers in the context of extreme weather by providing empirical evidence on AC demand in Turkish cities with different climates and population sizes.

The effect of extreme weather on AC demand is particularly interesting to study. On the one hand, extreme heat adversely affects the indoor conditions of buildings and the well-being of occupants, which in turn increases the need for mechanical cooling and the demand for ACs. On the other hand, with increasing need for mechanical cooling, the energy consumption of buildings increases, which in turn contributes to climate change through greenhouse gas emissions. Thus, the increasing demand for ACs has an impact on both the economy and the environment. We investigate the existence of interdependence between extreme temperatures and AC demand in Turkey. Turkey experienced a period of rapid economic growth from the early 2000s. We see clear evidence of income growth (GDP per capita) in the increase in demand for ACs in Turkey. However, other factors such as demographic and climatic conditions are also important in understanding this growth pattern, as the pace of AC demand growth is not uniform and varies across different regions of Turkey, presumably related to different climatic and socioeconomic conditions. The potential change in the city's exposure to extreme weather over time changes the nature of the household's decision to purchase an air conditioner. We tested and confirmed dynamic effects in our results, and to account for time (observations for 2005-2017) and cross-sectional variation (multiple cities/regions) in our data, as well as climatic/socioeconomic differences at the city level, we estimate an Autoregressive Distributed Lag (ARDL) dynamic panel specification. Within this framework, we can identify the short- and long-run effects of extreme weather on AC demand. We find strong evidence of a long-run equilibrium effect where consumer demand for ACs increased significantly due to extreme hot weather in Turkey. We checked our results with several measures of extreme heat constructed from our dataset. Our results support this finding.

The study contributes to the literature on the impact of extreme weather on consumer behavior by documenting the impact of extreme weather on consumer demand in a relatively unexplored market such as Turkey. In addition, the results inform companies of the benefits of understanding/studying the marginal effects of extreme weather through accurate measurement and analysis. For instance, in a market such as Turkey, the growth trend in the AC market could be overlooked, and all the credit could be given to demographics, and income growth. However, considering the occurrence of extreme weather events in a consistent modeling framework can yield significant insights. This paper is organized as follows. Section 2 presents a comprehensive literature review. Section 3 describes the data collection and the construction of the dataset. Section 4 outlines the empirical application, presents the results, and discusses their implications. Section 5 acknowledges the limitations and concludes with future research opportunities.

2. LITERATURE REVIEW

In recent years, an extensive body of research has emerged on the impact of extreme weather conditions on business and the economy. A wide range of industries such as agriculture, finance and insurance, healthcare, tourism, recreation, and leisure (TRL), transportation and public utilities such as electricity, gas and water, production systems and supply chains are affected by climate change and extreme weather events. On the supply side, the agriculture and food sectors are extremely vulnerable to extreme weather events such as extreme temperatures, droughts, wildfires, storms, and floods. While there are some studies assessing the impact of extreme weather on firm's financing decisions (Lee, Gino, and Staats, 2014), the bulk of the literature is concerned with the impact of extreme weather on agricultural insurance programs (Conradt, Finger, and Bokusheva, 2015; Furuya, Mar, Hirano and Sakurai, 2021; Xiao and Yao, 2019) and household insurance (Lucas, Booth, and Garcia, 2021). Extreme weather conditions affect not only supply, but also demand. Studies assess the demand response and price fluctuations of food and kindred products such as wheat and soybeans (Lybbert, Smith, and Sumner, 2014), bananas (Blake, Dawson, Loeillet, and Staver, 2018), and refreshment beverages (Keleş, Gómez-Acevedo, and Shaikh, 2018).

In the context of healthcare, studies assess the health impacts of extreme weather with time series analyses and quantify the public health impacts of extreme heat with real-life data on asthma admissions (Soyiri, Reidpath, and Sarran, 2013), emergency medical service calls (Calkins, Isaksen, Stubbs, Yost, and Fenske, 2016; Guo, 2017), emergency department visits (Wang et al. 2020), and police and fire service use (Williams, McDonogh-Wong, and Spengler 2020). A consensus quickly emerges that extreme heat has adverse effects on public health and healthcare services. For a detailed literature review, we refer the interested reader to Capari, Wilfing, Exner, Höflehner, and Haluza (2022).

The TRL industry does not only experience economic damage caused by extreme weather events (Liu, 2014; Dogru, Marchio, Bulut, and Suess, 2018), but is also subject to changing preferences of consumers due to extreme weather and climate change (Gómez-Martín, Armesto-López, and Martínez-Ibarra, 2014; Gössling, Abegg, and Steiger, 2016). Travel decisions to island destinations are particularly affected by climate change and climate-related extreme events (Hübner and Gössling, 2012; Susanto, Zheng, Liu, and Wang, 2020; Lam-González, Galindo, Hernández, and León, 2021). Hübner and Gössling (2012) and Lam-González et al. (2021) focus on the intention of decision makers; therefore, their unit of analysis is individuals, and they rely on a survey for data collection. Susanto et al. (2020) quantify the impacts of climate change on international tourism in Indonesia using real demand data. Oğur and Baycan (2022) assess the impact of extreme weather and climate change on real demand data and make projections for future tourism demand in Turkey, which is not an island but a peninsula.

The impact of the increasing number of extreme weather events on transportation services is two-fold: On the one hand, unexpected severe weather events delay or disrupt transportation services; on the other hand, demand response to extreme weather events is uncertain, complicating transportation system management and infrastructure planning. Studies employing surveys have reached a consensus that extreme weather events reduce travel demand, and the effect on recreational travel is more prominent (Sabir, van Ommeren, and Rietveld, 2013; Wu and Liao, 2020; Zanni, Goulden, Ryley, and Dingwall, 2017). Studies employing real demand data combined with meteorological data provide additional evidence on the impact of extreme weather on travel demand: Demand in commercial areas is less affected by extreme weather than demand in residential areas (Najafabadi, Hamidi, Allahviranloo, and Devineni, 2019), demand is more sensitive to extreme weather on weekend days as opposed to weekdays (Yang, Yue, Sun, Gao, and Wang, 2021) and during the day as opposed to night (Yue, Yang, Song, and Yuan, 2022), and demand response is affected not only by weather in the origin region but also by weather in the destination region, travel distances, and vehicle types (Yue,Yang, Song, and Yuan, 2022).

Extreme weather has a profound impact on public utilities such as electricity, gas, and water, as extreme weather events affect both supply and demand in the form of disruptions and abnormal peaks respectively. While there is a body of research focused on the impact of extreme weather on heat demand (Di Lascio, Menapace, and Righetti 2020; Aragon, James, Gauthier 2022), gas demand (Thornton et al. 2019), and renewable energy supply and demand (van der Wiel et al. 2019; Hasselqvist, Renström, Strömberg, and Håkansson, 2022; Moradi-Sepahvand, Amraee and Gougheri, 2022), the majority of studies deal with the impact of extreme weather on electricity demand, which can be categorized according to their research objective, namely forecasting short- and long-term demand (Garrido-Perez, Barriopedro, García-Herrera, and Ordóñez, 2021; Lee, 2022), assessing price responses (Fu, Allen, and Archibald, 2015; Bigerna, 2018), and understanding household consumption behavior (Harish, Singh, and Tongia, 2020; Silva, Soares, and Pinho, 2020; Liu, Zhang, Zhou, and Liao, 2021; Zhang, Guo, Smyth, and Yao, 2022). Extreme weather causes disruptions not only in power generation and distribution, but also in water supply due to the interconnected nature of service provision (Kayaga et al., 2021).

Although the impact of extreme weather and demand response has been studied in a variety of settings, the impact of extreme weather on the demand for durable goods has received little attention. Among durable goods, AC use has received the most attention, and rightly so. Due to climate change, average annual temperatures are increasing. This is expected to increase the likelihood of AC ownership and use, as well as energy consumption for indoor cooling. Salamanca et al. (2013) simulate AC electricity consumption during several extreme heat events in the Phoenix, USA, metropolitan area between 1961 and 2008 and evaluate their model with energy consumption data for 2008. They observe that energy consumption peaks in the evening hours, and that AC demand was up to 65% of the total hourly demand during heat waves. However, they do not observe any difference in demand patterns for weekdays and weekends.

De Cian, Pavanello, Randazzo, Mistry, and Davide (2019) match household data from the 2011 Environmental Policy and Individual Behaviour Change (EPIC) survey conducted by the Organization for Economic Cooperation and Development (OECD) with meteorological data from the following developed countries: Australia, Canada, France, Japan, the Netherlands, Spain, Sweden, and Switzerland. The authors employ univariate probit regressions to observe the adoption behavior of AC and thermal insulation. They find that the effect of climatic factors such as cooling degree days, days with temperatures above 18º C (64º F), demographics (gender, age, proportion of minors), household characteristics (tenure, ownership), and urbanization are more pronounced than the effect of income. Furthermore, AC adoption is more prominent than thermal insulation. This study uses cross-sectional data from different OECD countries with different climatic and socio-economic contexts.

Zhang, Sun, Fei, and Wei (2020) match household data from the 2014 Chinese Residents Energy Consumption Survey with meteorological data. For AC usage, they use annual AC usage time, average daily usage time, and AC cooling energy consumption, and for weather data, they use daily average temperature, precipitation, humidity, air pressure, and wind speed. Furthermore, they employ controls such as household size, household income, occupation and education of the household head, dwelling size, and year of construction. Since annual AC usage time and AC cooling energy consumption are continuous variables and average daily usage time is an ordinal variable, they employ OLS and probit models, respectively. Zhang, Sun, Fei, and We (2020) document that as temperature increases and/or high temperatures persist for a longer period of time, AC use time and cooling energy consumption increase. Furthermore, humidity, dwelling size, dwelling age, and occupation of the household head significantly affect AC usage time. Although the study by Zhang, Sun, Fei, and We (2020) is closely related to our study, it uses cross-sectional data.

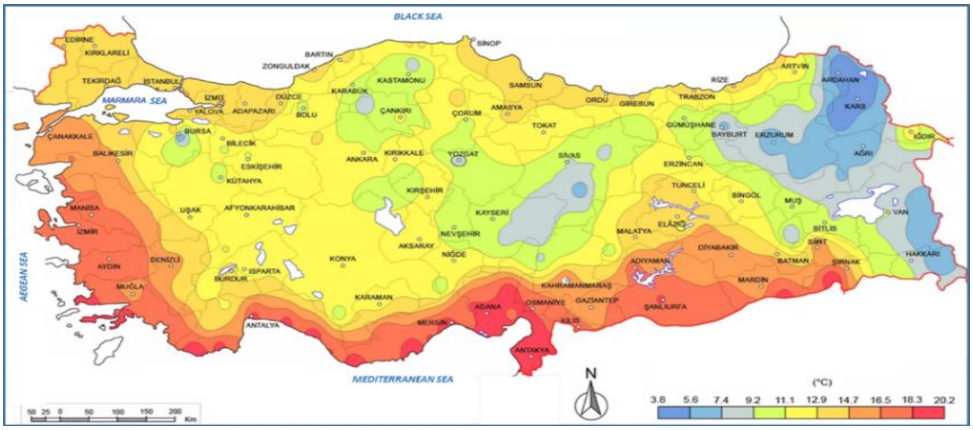
Castaño-Rosa et al. (2021) conduct a seven-country case study to project energy demand for cooling and heating in 2050. They incorporate in their analysis the share of households with air conditioning and the share of households that cannot cool comfortably in summer due to energy poverty. They also control for building age and energy performance certification. They assess people's adaptability and thermal comfort ranges according to the climatic characteristics of where they reside and estimate an increase in cooling energy demand even in northern countries, although not as much as in southern countries. The impact of extreme weather events on AC demand in the long run has been understudied. We aim to fill these gaps by conducting an empirical analysis based on consolidated data to understand the dynamics of AC demand. We employ a comprehensive panel data and dynamic models to investigate the effects of extreme heat and climate change on AC demand in the long run.

3. DATA AND VARIABLES

Weather data is obtained from the Turkish State Meteorological Service. The weather data includes information on annual average temperature, maximum temperature, and number of days above 30ºC (86ºF) for the period between 2005 and 2017. For AC demand, we employ market penetration as a proxy. Market penetration measures the extent to which a product or service is utilized by target customers relative to the total estimated market for that product or service. In applied industrial organization (IO) research, market shares often serve as proxies for aggregate demand, allowing for the examination of how various product characteristics, individual preferences, and firm strategies influence product demand. In this study, the share of households that own an air conditioner (AC) is used as a proxy for demand, expressed as a percentage of the target population. Nielsen provides time series data on the percentage of households with AC in various major cities in Turkey. This time series data, along with regional variations, is analyzed to understand the impact of extreme weather conditions on changes in demand structure.

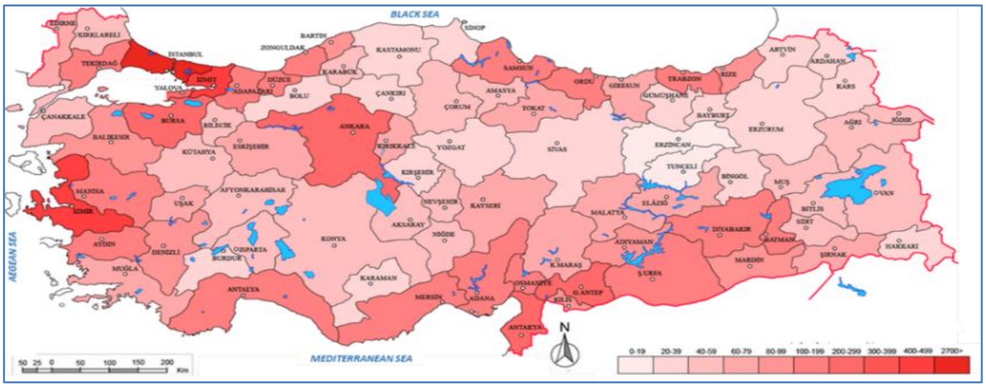
Turkey is divided into 7 geographical regions: Aegean, Black Sea, Central Anatolia, Eastern Anatolia, Marmara, Mediterranean, and Southeastern Anatolia. According to Figure 1, the highest average annual temperatures are observed in Southeastern Anatolia, Mediterranean and Aegean regions, moderate temperatures in Marmara, Central Anatolia and Black Sea regions and the lowest temperatures in Eastern Anatolia region. In addition to the regional climate, the population and purchasing power of the region are factors that affect the demand for AC. Figures 2 and 3 show the population and average GDP per capita. According to Figure 2, the highest populations are observed in the Marmara, Central Anatolia and Aegean regions and moderate to low populations in the Mediterranean, Black Sea and Southeastern Anatolia regions. As it can be seen in Figure 3, the average GDP per capita has a similar pattern to the population density. The Marmara, Central Anatolia and Aegean regions have the highest purchasing power, followed by the Mediterranean, Black Sea and Eastern Anatolia regions.

Figure 1. Annual Average Temperatures Between 1970 and 2015



Source: Turkish State Meteorological Service

Figure 2. Population Density in 2015



Source: Turkish Statistical Institute

Figure 3. Average GPD Per Capita in 2020

Source: Turkish Statistical Institute

In order for the final set to be representative in terms of regional climate, population density and purchasing power, we consider the population and GDP per capita of every city for each region. Based on the observations in the Appendix 1 we select the following cities: Aegean, Black Sea, Central Anatolia, Eastern Anatolia, Marmara, Mediterranean, and Southeastern Anatolia. İzmir for the Aegean region, Samsun for the Black Sea region, Ankara, Kayseri, Konya for the Central Anatolia, İstanbul, Bursa, Eskişehir, Kocaeli for the Marmara region, Adana, Antalya, Kahramanmaraş, Mersin for the Mediterranean region, Diyarbakır, Gaziantep, Şanlıurfa for the Southeast Anatolia. Due to the Eastern Anatolian climate, there is little or no demand for AC. Thus, we do not include any city from the Eastern Anatolian region in our analysis. Thereby, according to Turkish Statistical Institute (TUIK) 2017 data, the cities in the sample constitute 60% of Turkey's population and 71.5% of its GDP.

For city-specific controls, we employ the population of the city and the average gross domestic product per capita (GDPC) from the TUIK. The final dataset includes information on annual average temperature, maximum temperature, and number of days above 30ºC (86ºF) for 16 cities, and the dataset covers the period between 2005 and 2017. We plot annual averages to observe how key variables change over time. Figure 4 shows market penetration and weather conditions, and Figure 5 shows market penetration and population and purchasing power between 2005 and 2017.

Figure 4. Weather Conditions and Market Penetration Between 2011 and 2017

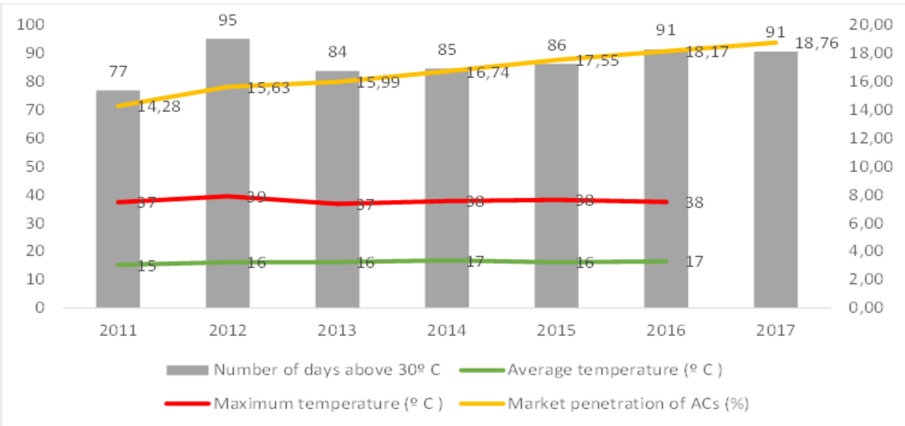
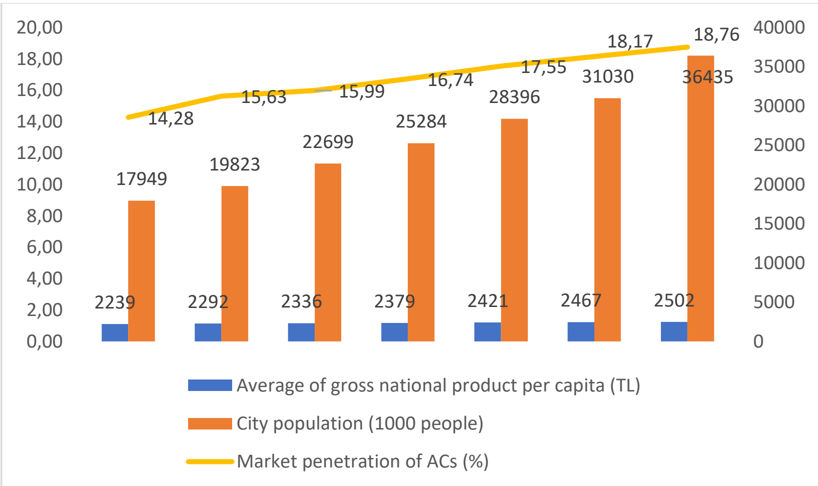


Figure 5. Population, Purchase Power and Market Penetration Between 2005 and 2017



We construct two additional measurements of extreme weather that incorporate people's thermal comfort bands according to the climatic characteristics of where they reside. First, we calculate the number of degrees that the maximum temperature deviates from the average temperature. Second, we weigh this measurement by the number of days above 30ºC. Summary statistics for the dataset are presented in Table 1.

Extreme heat 1 = Maximum temperature - Average temperature

*Extreme heat 2 = Extreme heat 1 * Number of days above 30ºC / 100*

Table 1. Summary Statistics

	Number of Observations	Mean	Std. dev.	Min.	Max.
Market Penetration (%)	208	13.28	5.87	2.3	27.2
Average Temperature (ºc)	185	16.23	2.81	10.1	21.4
Maximum Temperature (ºc)	187	38.44	3.01	30	45.2
Number of Days Above 30º C	205	89.02	37.19	1	154
Extreme Heat 1	184	22.21	3.53	13.6	29.7
Extreme Heat 2	184	19.95	8.98	0.157	40.004
City Population (1000 People)	196	2289.72	2955.22	718	14442.3
Average of Gross National Product Per Capita (TL)	208	19721.14	11712.49	3968	65041

Notes: The sample includes 16 cities over the period from 2005 to 2017, which would potentially produce a sample size of 208. City population data is missing for Eskisehir, Kahramanmaras, Kayseri, Kocaeli, Samsun, and Sanliurfa for the years 2005 and 2006. Extreme heat 1 and extreme heat 2 also have missing observations when the primary temperature data is unavailable. As a result, the estimation includes approximately 165 observations consisting of city-year pairs. The highest sample size for estimation is achieved using the maximum temperature measure, with a sample size of 184.

4. EMPIRICAL RESULTS AND DISCUSSION

It is expected that the cities with higher overall average temperatures over the year will have higher aggregate demand for ACs. Gross domestic product, population, and other city-level factors that are possibly correlated with temperature may also affect demand. Moreover, we need to capture the dynamics due to the changing nature of the household decision (to the extent that extreme temperatures may affect the decision to purchase an AC) and the possible change in the city's exposure to extreme weather over time. This latter effect will feed into households' decision-making process, as such, after episodes of extreme weather, and we might observe more actions in AC purchases. In addition, there are reasons to believe that the variables are not only contemporaneously related. Extreme weather events have become more frequent in recent decades (WMO, 2021) and are likely to affect the AC purchase decision not only for the current period but may cause a change in demand for future periods. We may observe a slow adjustment of households to temperature changes. This inertia is well known for many consumption decisions made by households (Xia and Li, 2010, Corbett and Tan, 2020), and a similar pattern could be expected for the AC purchase decision (MacKay and Remer, 2019). It is anticipated that the disutility from the increase in average temperatures and/or from the episodes of extreme temperatures may take a few years or longer to work through, as households may initially be uncertain whether these episodes (high temperatures) will be permanent or as intense as the year in which they were first experienced. Then the speed of adaptation to changing weather conditions will depend on the perception of whether the effect is expected to be permanent or transitory. This effect is also partially psychological, as some households may not believe that extreme temperatures are occurring more frequently than in the past, even though they experience such episodes. Similar behavior has been observed with public beliefs about climate change, for instance (Hall, 2019).

Such a framework requires the careful adaptation of time series estimation techniques to ensure considerations such as the stationarity of the series and the existence of a long-term relationship. The primary objective of this section is to highlight two critical aspects of extreme weather conditions on AC demand: (i) the importance of the chosen measure of extreme weather and (ii) the persistence of demand dynamics. The following section provides a formal treatment of both the time series and panel properties of our data, accompanied by the relevant tests.

4.1. Tests for Unit Roots (Panel Version)

Conducting unit root tests in a panel data setting involves certain assumptions and a comprehensive understanding of the data and the economic model in question. In our context, the panel structure is best characterized as having an infinite T and a finite N. Consequently, the asymptotics for the unit root tests should align with these specific assumptions. We utilize two sets of panel unit root tests to assess the stationarity of the variables employed. The first set employs a Fisher-type testing approach, where unit root tests are conducted for each panel individually. Subsequently, it combines the p-values from these tests to generate an overall test that supports Augmented Dickey-Fuller tests and Phillips-Perron tests as alternatives for each panel within the data. The null hypothesis for the Fisher-type tests is that the data contain a unit root. As noted by Hadri (2000), classical hypothesis testing requires strong evidence to reject the null hypothesis. Therefore, to provide a comprehensive assessment, we also conduct a test in which the null and alternative hypotheses are reversed, which helps to confirm or refute conclusions drawn from tests with the null hypothesis of non-stationarity.

Table 2. Panel Unit Root Tests

	Fisher-type unit-root test			
	Augmented Dickey–Fuller tests*		Phillips–Perron tests*	
AC Demand	3.1704	p-value = 0.9992	2.9801	p-value = 0.9986
Average temperature	2.9834	p-value = 0.9934	-7.8943	p-value = 0.0
Maximum temperature	1.3420	p-value = 0.9102	-9.4809	p-value = 0.0
Number of days above 30ºC	3.4332	p-value = 0.9997	-10.0784	p-value = 0.0
Extreme heat 1	3.4705	p-value = 0.9997	-9.8196	p-value = 0.0
Extreme heat 2	-1.5408	p-value = 0.0617	-9.4852	p-value = 0.0
log (Average GDPC)	-1.3083	p-value = 0.0954	0.4540	p-value = 0.6751
log (City population)	-1.4867	p-value = 0.0686	0.6294	p-value = 0.7355
*Z-value is reported	H0: All panels contain unit roots		Ha: At least one panel is stationary	

However, it is important to note a caveat of the Hadri LM test, which requires that the panels be strongly balanced. In addition, we employ the Hadri LM stationarity test specifically for variables within a balanced panel. The outcomes of the panel unit root tests are detailed in Table 2. The outcomes presented in Table 2 indicate the potential presence of unit roots in certain variables across specific panels. Notably, variables such as income per capita and population exhibit unit roots across panels, highlighting the need to adjust for this in the analysis. Consequently, our next step involves investigating the possibility of a panel cointegration relationship. To delve deeper into the dynamics at play, we conduct tests specifically designed to examine the existence of a cointegration relationship within the panel data. This exploration is crucial for unraveling the interdependencies and long-term associations among the variables, thus contributing to a more comprehensive understanding of the underlying economic dynamics.

4.2. Tests for Panel Cointegration

We conduct cointegration tests on a panel dataset using the methodologies of Kao (1999), Pedroni (1999, 2004), and Westerlund (2005). These tests allow for the inclusion of panel-specific means (fixed effects) and panel-specific time trends in the cointegrating regression model. Different versions of the tests are performed, with the most common specifications reported in Table 3 and Appendix 2. The null hypothesis for all tests is the absence of cointegration, while the alternative hypothesis for the Kao and Pedroni tests is cointegration across all panels. The Westerlund test is performed in two versions - one suggesting cointegration in some panels and the other suggesting cointegration in all panels. The test outcomes provide substantiated evidence for the presence of a cointegration relationship in our dataset. We then proceed to estimate the dynamic fixed effects model.

Table 3. Panel Cointegration Tests

Kao test for Cointegration	Average temperature	Maximum temperature	Number of days above 30ºC	Extreme heat 1	Extreme heat 2
Modified DF	-0.3725	-0.4308	-0.3975	0.3764	-0.2665
Dickey–Fuller	-2.0763**	-2.1134**	-2.1897**	-1.5236*	-1.9835**
Augmented DF*	-3.4982***	-3.4281***	-3.0329***	-2.6343***	-3.205***
Unadjusted Modified DF	-0.9981	-1.2273	-1.6227*	-1.0193	-0.9677
Unadjusted DF	-2.4596***	-2.5947***	-2.9288***	-2.5078***	-2.4222***

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

H_0: No cointegration H_a: All panels are cointegrated

Note: Kao (1999) is reported in Table 3 for the cointegration relationships of the variables; demand (perctAC), respective extreme weather variable (avgtemp, maxtemp, over30Cdays, DegreesOAvg, Wover30Cdays), log gross national product (loggdpc) and log city population (logpop).

4.3 Dynamic ARDL Results

A complete estimation framework should consider the time series dynamics in a consistent manner and identify the effect of extreme weather accordingly. For this reason, we estimate a dynamic panel model, and only with this model, we have the framework to distinguish between the short-run and long-run effects of extreme weather on AC demand (Pesaran, Shin, and Smith, 1997, 1999, Pesaran and Smith, 1995, Phillips and Moon, 2000). Of these effects, we are mostly interested in the long-run, as this relationship can verify the equilibrium effect of extreme weather on AC demand. The estimation framework we use is known as dynamic panel estimation. The relationship between AC demand and the extreme events variable is an Autoregressive Distributed Lag (ARDL) dynamic panel specification with the following form.

$$C_{it} = \sum_{s=1}^{p} \beta_{is}\, C_{i,t-s} + \sum_{s=0}^{q} \delta'_{is} X_{i,t-s} + \mu_i + \epsilon_{it} \quad (1)$$

where the number of cities $i = 1, \dots N$; the number of time periods $t = 1, \dots T$; C_{it} is the AC demand in city i in period t; $X_{i,t}$ is a k × 1 vector of explanatory variables including the weather variable ; δ'_{it} are the k × 1 coefficient vectors; β_{is} are scalars; and μ_i are the city-specific effects. T is large enough that the model can be fitted separately for each city. Our interest in this paper is to find the long-run effect of extreme weather on AC demand.

$$C_{it} = \alpha + \theta' X_{it} + u_{it} \quad (2)$$

The specification in (2) captures the long-run dynamics of the relationship. In addition, short-run effects (if they are significant) are of interest to understand the factors specific to the relationship. The results of these analyses can be obtained at the city level. Furthermore, equation 1 can be extended to jointly model the long-run and short-run dependence if the variables in (1) are, for example, I (1). The error correction representation of the panel ARDL model is as follows.

$$\Delta C_{it} = \emptyset_i\left(C_{i,t-1} - \alpha - \theta' X_{i,t-1}\right) + \sum_{s=1}^{p-1} \beta^*_{i,t-s}\, \Delta C_{i,t-s} + \sum_{s=0}^{q-1} \delta'_{is} \Delta X_{i,t-s} + \mu_i + \epsilon_{it} \quad (3)$$

The parameter $\emptyset_i$ is the error-correcting speed of the adjustment term. If this coefficient is equal to zero, then there would be no evidence of a long-run relationship. Within the parameterization in (3), $\emptyset$ is expected to be significantly negative for the ARDL specification to have a long-run equilibrium. We are interested in the parameter θ because the existence of a long-run response is depicted by the magnitude (and possibly the sign) of this parameter. We estimate equation (3) to examine the short-run and long-run (cointegration) interactions between the variables of interest.

In our empirical set-up, our main estimation equation includes the AC demand as the C_{it} variable and $X_{i,t}$ is 3 × 1 vector consisting of variables for extreme weather, city-level income and population.

We obtained the optimal lag length in the error correction model (ARDLC) by starting with a large p and q to drop insignificant stationary regressors[1].

Several restrictions can be imposed on the estimation of equation (3). We estimate a dynamic fixed effect (DFE) estimator where all parameters in (3), except the intercepts, are constrained to be equal across panels[2]. With this estimator, all short-run and long-run coefficients are restricted to come from a common source of data generation process postulated by the dynamics of the effect of extreme temperature on AC demand. The other extreme modeling choice would be to allow all parameters to be panel (city) specific. However, this specification would be undesirable in our setting, both because of data limitations, but also because we believe that the long-run and short-run dynamics for AC demand should be similar for the AC demand equation for each city once the city and macro-level fixed factors are controlled for. The latter is in the spirit of the basic economic modeling of the demand equation based on the consumer choice specification (Stone, 1954, Hands, 2010, Gowdy and Mayumi, 2001). Moreover, we compute the Hausman test to compare the DFE estimator with a mean group (MG) estimator that fits the parameters as averages of the N individual group regressions. In other words, the MG estimator fits the model separately for each city and takes the arithmetic mean of the coefficients. Computationally less burdensome (but theoretically less attractive), this estimator allows us to see the range of the relationship at the city level. The Hausman test rejects the MG estimator with a value of 0.02 and a p-value of 0.9995. Therefore, our results suggest that the simultaneous equation bias is minimal, and we prefer the FE model to the MG model.

Table 4. Dynamic Fixed Effect Results

Dependent Variable: AC Demand					
Long Run					
X:	Number of days above 30º	Average temperature	Maximum temperature	Extreme heat 1	Extreme heat 2
X	0.117**	-0.619	0.570**	0.662***	0.630***
log (Average GDPC)	5.091***	4.571***	5.986***	4.941***	6.179***
log (City population)	3.077	10.17	7.389	14.56*	14.08*
Short Run					
CoinTerm	-0.434***	-0.473***	-0.518***	-0.458***	(0.0673)

[1] Similar to Pesaran and Shin (1998) the Schwarz information criterion (SIC) is used. For robustness, the Akaike information Criterion (AIC) is employed. A general-to-specific approach (starting with p = 4 and q = 4 to drop insignificant stationary regressors) is adopted to choose the optimal lag length for the analyses.

[2] To be able to use the panel ARDL model, our variables should be integrated of order 1 or higher and have a cointegration relationship. We test the cointegration hypothesis using the panel versions of the cointegration test (Kao, 1999). Specifically, we use the Kao test for cointegration, which reports various test results with a null hypothesis constructed as no cointegration relationship in all panels. The alternative hypothesis is that all panels are cointegrated. The results show strong evidence of cointegration in most panels as the Unadjusted Dickey-Fuller t has a p-value of 0.008, the Augmented Dickey-Fuller t has a p-value of 0.0007 and the Dickey-Fuller t has a p-value of 0.0237. The unadjusted modified Dickey-Fuller t shows some evidence of weak cointegration in some panels, as the p-value is 0.1666. However, taking all the test results together, we conclude that a cointegration relationship exists and the panel ARDLC model is suitable for modeling the long run relationship.

LD. AC Demand	-0.0706	-0.118	-0.0272	-0.0496	-0.00769
D. Number of days above	-0.0360**				
D. Average temperature		-0.0149			
D. Maximum temperature			-0.229**		
D. Extreme heat 1				-0.167**	
D. Extreme heat 2					-0.195***
LD. Number of days above	-0.0201*				
LD. Average temperature		-0.126			
LD. Maximum temperature			-0.115*		
LD. Extreme heat 1				-0.0772	
LD. Extreme heat 2					-0.0999***
D. log (Average GDPC)	6.138***	4.570*	6.310***	5.927***	8.900***
D. log (City population)	-4.818	-8.609	-12.71	-12.43	-6.924
Constant	-29.48	-44.51*	-62.09**	-70.99***	-74.77***
Observations	166	166	184	165	165
R-squared	0.986	0.986	0.987	0.986	0.986
Standard errors in brackets. Time FE are included.					
*** p<0.01, ** p<0.05, * p<0.1					

4.4. Discussion

In Table 4, we estimate the dynamic fixed effects model and report the results with the appropriate lags included and the long run relationship modeled. The main relationship we are interested in is the long-run equation. The top panel of Table 4 shows the results of the long-run equilibrium relationship. The coefficients in these equations are as described in equation (2). We observe that all of the long-run coefficients for the weather variables are significant except for the average temperature in column (2), which is not surprising given that the average temperature is a measure averaged over a year and should not contain any information in predicting the long-run demand for ACs. For the equation in the first column using the number of days above 30ºC variable (which measures the number of days with temperatures above 30ºC), the long run relationship is as follows.

$$ACDemand_{it} = 0.117 \times Number\ of\ days\ above\ 30º\ C_{it} + 5.091 \times log\ (Average\ GDPC)_{it} + 3.077 \times log\ (City\ population)_{it}$$

The coefficient is statistically significant and can be interpreted as an increase of 1 day in the number of days with temperatures above 30ºC will, in the long-run, increase the demand for AC by 0.117 percentage points. In the same fashion an increase of 10 days in the number of days with temperatures above 30ºC will, in the long-run, increase the demand for AC by 1.17 percentage points. This means that for the city of Istanbul, for example, the percentage of households with AC should increase from 27.1% to 28.27% just because of an increase of 10 days in the number of days with temperatures above 30ºC[3]. According to the Turkish Statistical Institute, the number of households in Istanbul in 2018 was 4,596,419. Therefore, an increase of 1.17% would mean the addition of 53,778 households for AC ownership and use. The average hourly power consumption of 24,000 BTU AC units is 318 watts[4]. If we assume that on average each household uses their AC for one hour per day and 90 days per year, we observe an increase in energy consumption of 1539.13 MWh. In Turkey, approximately 20% of the energy generation is from renewable sources, while the rest is from fossil fuels such as oil, coal and natural gas. The CO_2 emission of electricity generated from fossil fuels is estimated to be 0.492 ton CO_2/MWh. We can safely assume that 1,231.3 MWh out of 1,539.13 MWhs are produced from fossil fuels and the corresponding annual CO_2 emissions would be 605.8 tons. For the equation in the fourth column, using Extreme Heat 1 (which measures the number of degrees that the maximum temperature deviates from the average temperature), the relationship is as follows:

$$ACDemand_{it} = 0.662 \times Extreme\ heat\ 1_{it} + 4.941 \times log\ (Average\ GDPC)_{it} \\ + 14.56 \times log\ (City\ population)_{it}$$

The coefficient is statistically significant and can be interpreted as an increase of 1ºC in the number of degrees the maximum temperature deviates from the average temperature increases the AC demand by 0.662 percentage points in the long-term. For example, for the city of Istanbul, the percentage of households with AC should increase from 27.1% to 27.76%. An increase of just 1ºC would result in 30,428 more households using AC. We make the same assumptions on AC usage (one hour per day and 90 days per year) and energy source (80 produced from fossil fuels), the corresponding increase in the electricity consumption and pollution associated with a 0.662% increase in AC usage would be 870,86 MWh and 342,77 tons of CO_2 emissions, respectively. The coping mechanism for the increasing occurrence of extreme heat causes more extreme heat, leading to a vicious cycle.

This study has practical implications for the AC market and policy implications. Turkey has a lot of room for growth as the average market penetration is 13.3% with a maximum penetration of 27.2 % in Ankara. Thus, the economic and environmental consequences of potential high AC usage should be evaluated by policymakers and reacted to proactively with policies targeting the impact of extreme hot weather on households' preferences. Encouraging the use of high-efficiency ACs, improving the thermal conditions of buildings by implementing strict energy performance standards for new buildings and energy improvement measures for existing buildings, and the long-term planning of energy infrastructure may be more important than ever because of extreme weather events. As listed above, incentivizing the use of high-efficiency ACs through the market (tax benefits), regulating the energy performance standards for new/existing buildings are some of the alternative policies that can be employed. Otherwise, as our results demonstrate, consumer preferences seem to respond to extreme

[3] We control for income and population, as well as the trends in the demand due to city related fixed effects and macro level shocks (time fixed effects are eliminated in the differenced form in the estimation).
[4] https://www.kompulsa.com/much-power-air-conditioners-consume/

weather by increasing the demand for ACs, which is likely to have dire consequences both economically and environmentally.

5. CONCLUSION

Previous research highlights the important role of extreme weather events in consumer behavior. However, there is still a need for more country-specific evidence in product markets, especially from emerging economies. In our study, using panel data - from several cities over time - we created a decent sample to study the effect of extreme weather on AC demand in the Turkish market. In doing so, we examined both time and cross-sectional variation in the data to identify the short- and long-run impacts of extreme hot weather conditions in a cointegration approach (ARDL model). Our findings suggest a long-term relationship between extreme hot weather and AC demand in Turkey. We tested this result with different definitions of extreme weather conditions and confirmed the robustness of this finding. Methodologically, dynamic panel estimation allowed us to obtain these important results. We show and test the importance of time series dynamics and discuss the possible sources of these dynamics, such as the slow adjustment of households to temperature changes. We argue that this inertia, which is well documented for many consumer goods purchased by households, is also valid for the AC purchase decision. We propose a complete estimation framework that considers both the time series dynamics in a consistent manner and identifies the effect of extreme weather on AC demand as a long-run equilibrium relationship.

This study has several limitations that need to be addressed. First, we mainly focused on the effect of extreme heat on AC use, and due to data limitations, the potential effects of other climatic factors such as humidity, wind, and precipitation were not considered. Future research could examine the effect of both extremes and incorporate other climatic factors into the analysis. Further controls could be added, such as the number of air conditioner advertisements, air-conditioner prices, and electricity prices. A possible extension could be a model that considers the spatial dependence of demand across cities. The empirical analysis is based on panel data for the years 2005-2017. On the one hand, the dynamic aspect of climate change would be better served by longer and more recent time series. On the other hand, it is more desirable to study such relationships in a more stable economic period than in an era such as the COVID-19 period. In the COVID-19 period, the extremity of the period affects consumer decision making. Therefore, the pre-COVID-19 period can serve as a better balance for our research design, where demand decisions can be attributed to long-term effects. Finally, the findings are limited to the Turkish AC market and its surrounding climatic and socio-economic context. Therefore, the findings should be generalized to the emerging market context with this consideration.

REFERENCES

Aragon, V., James, P.A.B. And Gauthier, S. (2022) "The Influence of Weather on Heat Demand Profiles in UK Social Housing Tower Blocks", Building and Environment, 219: 109101. Doi: 10.1016/J.Buildenv.2022.109101

Bigerna, S. (2018) "Estimating Temperature Effects on the Italian Electricity Market", Energy Policy, 118: 257-269. Doi: 10.1016/J.Enpol.2018.03.068

Blake, D., Dawson, C., Loeillet, D. and Staver, C. (2018) "Can Global Climate Change Affect Prices in The World Banana Market?", German Journal of Agricultural Economics, 67(1): 48-64. Doi: 10.22004/Ag.Econ.309949

Calkins, M.M., Isaksen, T.B., Stubbs, B.A., Yost, M. G. and Fenske, R. A. (2016) "Impacts of Extreme Heat on Emergency Medical Service Calls in King County, Washington, 2007–2012: Relative Risk and Time Series Analyses of Basic and Advanced Life Support", Environmental Health, 15:13.

Capari, L., Wilfing, H., Exner, A., Höflehner, T. and Haluza, D. (2022) "Cooling the City? A Scientometric Study on Urban Green and Blue Infrastructure and Climate Change-Induced Public Health Effects", Sustainability, 14: 4929. Doi:10.3390/Su14094929

Castaño-Rosa, R., Barrella, R., Sánchez-Guevara, C., Barbosa, R., Kyprianou, I., Paschalidou, E., Thomaidis, N.S., Dokupilova, D., Gouveia, J.P., Kádár, J., Hamed, T.A. and Palma, P. (2021) "Cooling Degree Models and Future Energy Demand in the Residential Sector. A Seven-Country Case Study", Sustainability, 13: 2987. Doi: 10.3390/Su13052987

Conradt, S., Finger, R. And Bokusheva, R. (2015) "Tailored to the Extremes: Quantile Regression for Index-Based Insurance Contract Design", Agricultural Economics, 46: 537-547. Doi: 10.1111/Agec.12180

Corbett P. And Tan, A. (2020) "Demand Orientation in A World of Demand Inertia. Deloitte Australia Blog", Link: Https://Www2.Deloitte.Com/Au/En/Blog/Strategy-Blog/2020/Demand-Orientation-In-World-Of-Demand-Inertia.Html, (09/27/2022)

De Cian, E., Pavanello, F., Randazzo, T., Mistry, M. N. and Davide, N. (2019) "Households' Adaptation in A Warming Climate. Air Conditioning and Thermal Insulation Choices", Environmental Science & Policy, 100: 136-157. Doi: 10.1016/J.Envsci.2019.06.015.

Di Lascio, F.M.L., Menapace, A. and Righetti, M. (2020) "Joint and Conditional Dependence Modelling of Peak District Heating Demand and Outdoor Temperature: A Copula-Based Approach", Statistical Methods & Applications, 29: 373–395. Doi:10.1007/S10260-019-00488-4

Dogru, T., Marchio, E. A., Bulut, U. and Suess, C. (2019) "Climate Change: Vulnerability and Resilience of Tourism and the Entire Economy", Tourism Management, 72: 292–305. Doi: 10.1016/J.Tourman.2018.12.010

Fu, K.S., Allen, M.R. and Archibald, R.K. (2015) "Evaluating the Relationship Between the Population Trends, Prices, Heat Waves, And the Demands Of Energy Consumption In Cities", Sustainability, 7: 15284-15301. Doi:10.3390/Su71115284

Furuya, J., Mar, S.S., Hirano, A. and Sakurai, T. (2021) "Optimum Insurance Contract of Flood Damage Index Insurance for Rice Farmers in Myanmar", Paddy and Water Environment, 19: 319–330. Doi:10.1007/S10333-021-00859-2

Garrido-Perez, J.M., Barriopedro, D., García-Herrera, R. and Ordóñez, C. (2021) "Impact of Climate Change on Spanish Electricity Demand", Climatic Change, 165: 50. Doi:10.1007/S10584-021-03086-0

Gómez-Martín, M.B., Armesto-López, X.A. and Martínez-Ibarra, E. (2014) "The Spanish Tourist Sector Facing Extreme Climate Events: A Case Study of Domestic Tourism in the Heat Wave Of 2003", International Journal of Biometeorology, 58: 781–797. Doi:10.1007/S00484-013-0659-6

Government of Pakistan, National Disaster Management Authority, 2022, Daily Weather & Flood Situation Report Dated 20th September 2022. Link: Http://Cms.Ndma.Gov.Pk/Storage/App/Public/Situation-Reports/September2022/2rjgbn4gtvjgzoznyly0.Pdf, (09/27/2022)

Gowdy, J. M. and Mayumi K. (2001) "Reformulating the Foundations of Consumer Choice Theory and Environmental Valuation", Ecological Economics, 39 (2): 223-237. Doi:10.1016/S0921-8009(01)00197-5

Gössling, S., Abegg, B. and Steiger, R. (2016) "It Was Raining All the Time! Ex Post Tourist Weather Perceptions", Atmosphere, 7(1): 10. Doi:10.3390/Atmos7010010

Guo, Y. (2017) "Hourly Associations Between Heat and Ambulance Calls", Environmental Pollution, 220 (Pt B): 1424-1428. Doi: 10.1016/J.Envpol.2016.10.091

Hadri, K. (2000) "Testing for Stationarity in Heterogeneous Panel Data", Econometrics Journal, 3(2): 148-161. Doi: 10.1111/1368-423X.00043

Hall, D. (2019) "Climate Explained: Why Some People Still Think Climate Change Isn't Real", Climate Explained, Link: Https://Theconversation.Com/Climate-Explained-Why-Some-People-Still-Think-Climate-Change-Isnt-Real-124763, (09/27/2022).

Hands, D. W. (2010) "Economics, Psychology and the History of Consumer Choice Theory", Cambridge Journal of Economics, 34(4): 633–648. Doi: 10.1093/CJE/BEP045

Harish, S., Singh, N. and Tongia, R. (2020) "Impact of Temperature on Electricity Demand: Evidence from Delhi And Indian States", Energy Policy, 140: 111445. Doi: 10.1016/J.Enpol.2020.111445

Hasselqvist, H., Renström, S., Strömberg, H. and Håkansson, M. (2022) "Household Energy Resilience: Shifting Perspectives to Reveal Opportunities for Renewable Energy Futures in Affluent Contexts", Energy Research & Social Science, 88: 102498. Doi: 10.1016/J.Erss.2022.102498

Hübner, A. and Gössling, S. (2012) "Tourist Perceptions of Extreme Weather Events in Martinique", Journal of Destination Marketing & Management, 1(1–2): 47-55. Doi: 10.1016/J.Jdmm.2012.09.0

Kao, C. (1999) "Spurious Regression and Residual-Based Tests for Cointegration In Panel Data", Journal of Econometrics, 90: 1-44. Doi: 10.1016/S0304-4076(98)00023-2

Kayaga, S. M., Amankwaa, E. F., Gough, K. V., Wilby, R. L., Abarike, M. A., Codjoe, S. N. A., Kasei, R., Nabilse, C. K., Yankson, P. W. K., Mensah, P., Abdullah, K. and Griffiths, P. (2021) "Cities and Extreme Weather Events: Impacts Of Flooding And Extreme Heat On Water And Electricity Services In Ghana", Environment And Urbanization, 33(1): 131–150. Doi:10.1177/0956247820952030

Keleş, B., Gómez-Acevedo, P. and Shaikh, N. I. (2018) "The Impact of Systematic Changes in Weather on the Supply and Demand of Beverages", International Journal of Production Economics, 195: 186-197. Doi: 10.1016/J.Ijpe.2017.08.002

Komesaroff, P. and Kerridge, I. A. (2020) "Continent Aflame: Ethical Lessons from the Australian Bushfire Disaster", Bioethical Inquiry, 17:11–14. Doi: 10.1007/S11673-020-09968-9

Lam-González, Y.E., Galindo, C.G., Hernández, M.M.G. and León, C.J., (2021) "Understanding the Heterogeneity of Tourists' Choices Under Climate Change Risks: A Segmentation Analysis", Atmosphere, 12: 22. Doi:10.3390/Atmos12010022

Lange, J. and Gillespie, J. (2022) "Bushfire, Prescribed Burning, and Non-Human Protection", Geographical Research, 1– 24. Doi:10.1111/1745-5871.12558

Lee, J. J., Gino, F. and Staats, B. R. (2014) "Rainmakers: Why Bad Weather Means Good Productivity", Journal of Applied Psychology, 99 (3): 504-513. Doi:10.1037/A0035559

Lee, J. (2022) "The Impact of Neglecting Climate Change and Variability on ERCOT's Forecasts of Electricity Demand in Texas", Weather, Climate, And Society, 14(2). Doi:10.1175/WCAS-D-21-0140.1

Liu T-M. (2014) "Analysis of the Economic Impact of Meteorological Disasters on Tourism: The Case of Typhoon Morakot's Impact on the Maolin National Scenic Area in Taiwan", Tourism Economics, 20(1): 143-156. Doi:10.5367/Te.2013.0258

Liu, X.-Q., Zhang, C., Zhou, Y. and Liao, H. (2021) "Temperature Change and Electricity Consumption of the Group Living: A Case Study of College Students", Science of the Total Environment, 781: 146574.

Lucas, C.H., Booth, K.I. and Garcia, C. (2021) "Insuring Homes Against Extreme Weather Events: A Systematic Review of the Research", Climatic Change, 165: 61. Doi:10.1007/S10584-021-03093-1

Lybbert, T.J., Smith, A. and Sumner, D.A. (2014) "Weather Shocks and Inter-Hemispheric Supply Responses: Implications for Climate Change Effects on Global Food Markets", Climate Change Economics, 05: 1450010.

Mackay, A. and Remer, M. (2019) "Consumer Inertia and Market Power", Harvard Business School, Working Paper 19-111. Doi: 10.2139/Ssrn.3380390

Moradi-Sepahvand, M., Amraee, T. and Gougheri, S. S. (2022) "Deep Learning Based Hurricane Resilient Coplanning of Transmission Lines, Battery Energy Storages, and Wind Farms", IEEE Transactions on Industrial Informatics, 18(3): 2120-2131. Doi: 10.1109/TII.2021.3074397

Najafabadi, S., Hamidi, A., Allahviranloo, M. and Devineni, N. (2019) "Does Demand for Subway Ridership in Manhattan Depend on the Rainfall Events?", Transport Policy, 74: 201-213. Doi: 10.1016/J.Tranpol.2018.11.019.

Oğur, A. A. and Baycan, T. (2022) "Assessing Climate Change Impacts on Tourism Demand in Turkey", Environment, Development and Sustainability. Doi:10.1007/S10668-022-02135-7

Pedroni, P. (1999) "Critical Values for Cointegration Tests in Heterogeneous Panels with Multiple Regressors", Oxford Bulletin of Economics and Statistics, 61: 653-670. Doi: 10.1111/1468-0084.0610s1653

Pedroni, P. (2004) "Panel Cointegration: Asymptotic and Finite Sample Properties of Pooled Time Series Tests with An Application to The PPP Hypothesis", Econometric Theory, 20 (3): 597-625. Doi:10.1017/S0266466604203073

Pesaran, M.H. and Shin, Y. (1998) "An Autoregressive Distributed-Lag Modelling Approach to Cointegration Analysis", Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium, 31: 371-413. Doi:10.1017/CCOL0521633230.011

Pesaran, M. H., Shin, Y. and Smith, R. P. (1997) "Estimating Long-Run Relationships in Dynamic Heterogeneous Panels", DAE Working Papers Amalgamated Series, 9721.

Pesaran, M. H., Shin, Y. and Smith, R. P. (1999) "Pooled Mean Group Estimation of Dynamic Heterogeneous Panels", Journal of the American Statistical Association, 94: 621-634. Doi: 10.2307/2670182

Pesaran, M. H. and Smith, R. P. (1995) "Estimating Long-Run Relationships from Dynamic Heterogeneous Panels", Journal of Econometrics, 68: 79-113. Doi: 10.1016/0304-4076(94)01644-F

Phillips, P. C. B. and Moon, H. R. (2000) "Nonstationary Panel Data Analysis: An Overview of Some Recent Developments", Econometric Reviews, 19: 263-286. Doi: 10.1080/07474930008800473

Sabir, M., Van Ommeren, J. and Rietveld, P. (2013) "Weather to Travel to the Beach", Transportation Research Part A: Policy and Practice, 58, 79-86. Doi: 10.1016/J.Tra.2013.10.003

Salamanca, F., Georgescu, M., Mahalov, A., Moustaoui, M., Wang, M. and Svoma, B. M. (2013) "Assessing Summertime Urban Air Conditioning Consumption in A Semiarid Environment", Environmental Research Letters, 8 (3): 034022. Doi: 10.1088/1748-9326/8/3/034022

Silva, S., Soares, I. and Pinho, C. (2020) "Climate Change Impacts on Electricity Demand: The Case of a Southern European Country", Utilities Policy, 67: 101115. Doi: 10.1016/J.Jup.2020.101115

Soyiri, I.N., Reidpath, D.D. and Sarran, C. (2013) "Forecasting Peak Asthma Admissions in London: An Application of Quantile Regression Models", International Journal of Biometeorology, 57: 569–578. Doi:10.1007/S00484-012-0584-0

Stone, J. (1954) "Linear Expenditure Systems and Demand Analysis: An Application to the Pattern of British Demand", Economic Journal, 64: 511–527.

Susanto, J., Zheng, X., Liu, Y. and Wang, C. (2020) "The Impacts of Climate Variables and Climate-Related Extreme Events on Island Country's Tourism: Evidence from Indonesia", Journal of Cleaner Production, 276: 124204. Doi: 10.1016/J.JCLEPRO.2020.124204

Thornton, H.E., Scaife, A.A., Hoskins, B.J., Brayshaw, D.J., Smith, D.M., Dunstone, N., Stringer, N. and Bett, P. E. (2019) "Skilful Seasonal Prediction of Winter Gas Demand", Environmental Research Letters, 14 (2): 024009. Doi:10.1088/1748-9326/Aaf338

UNDRR (2020) "Human Cost of Disasters: An Overview of the Last 20 Years 2000-2019", United Nations Office for Disaster Risk Reduction, Geneva, Switzerland.

United Nations Environmental Programme (2004) "Impacts of Summer 2003 Heat Wave in Europe", Environment Alert Bulletin, 2, 1-4.

Van Der Wiel, K., Bloomfield, H., Lee, R., Stoop, L., Blackport, R., Screen, J. Et Al. (2019) "The Influence of Weather Regimes on European Renewable Energy Production and Demand", Environmental Research Letters, 14 (9): 094010. Doi:10.1088/1748-9326/Ab38d3

Wang,Y., Liu, Y., Ye, D., Li, N., Bi, P., Tong, S., Wang, Y., Cheng, Y., Li, Y. and Yao, X. (2020) "High Temperatures and Emergency Department Visits in 18 Sites with Different Climatic

Characteristics In China: Risk Assessment and Attributable Fraction Identification", Environment International, 136: 105486.

Westerlund, J. (2005) "New Simple Tests for Panel Cointegration", Econometric Reviews, 24 (3): 297-316.

Williams, A., Mcdonogh-Wong, L. and Spengler, J. D. (2020) "The Influence of Extreme Heat on Police and Fire Department Services In 23 U.S. Cities", Geohealth, 4. Doi:10.1029/2020GH000282

World Meteorological Organization (WMO) (2021) "Weather-Related Disasters Increase Over Past 50 Years, Causing More Damage but Fewer Deaths", Link: Https://Public.Wmo.Int/En/Media/Press-Release/Weather-Related-Disasters-Increase-Over-Past-50-Years-Causing-More-Damage-Fewer 09/27/2022.

Wu, J. and Liao, H. (2020) "Weather, Travel Mode Choice, and Impacts on Subway Ridership in Beijing", Transportation Research Part A: Policy and Practice, 135: 264-279. Doi: 10.1016/J.Tra.2020.03.020

Xia, T. and Li, X. (2010) "Consumption Inertia and Asymmetric Price Transmission", Journal of Agricultural and Resource Economics, 35 (2): 209–227. Doi: 10.22004/Ag.Econ.93210

Xiao, Y. and Yao, J. (2019) "Double Trigger Agricultural Insurance Products with Weather Index and Yield Index.", China Agricultural Economic Review, 11 (2): 99-316. Doi:10.1108/CAER-01-2018-0021

Yang, X., Yue, X., Sun, H., Gao, Z. and Wang, W. (2021) "Impact of Weather on Freeway Origin-Destination Volume in China", Transportation Research Part A: Policy and Practice, 143: 30-47. Doi: 10.1016/J.Tra.2020.11.007

Yue, X., Yang, X., Song, D. and Yuan, Y. (2022) "The Interaction Effect of Severe Weather and Non-Weather Factors on Freeway Travel Volume", Science of the Total Environment, 808: 152057, Doi: 10.1016/J.Scitotenv.2021.152057

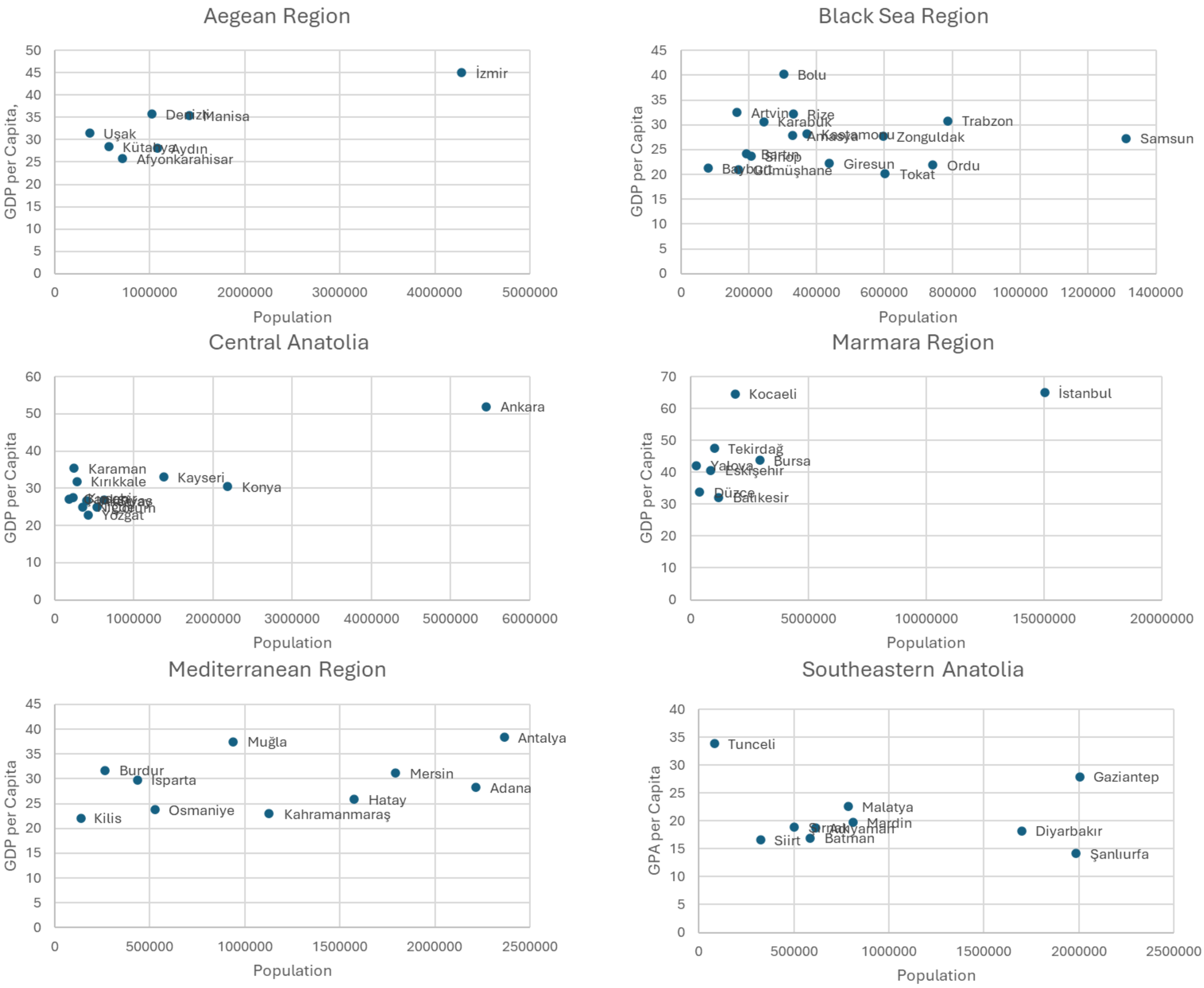
Zanni, A. M., Goulden, M., Ryley, T. and Dingwall, R. (2017) "Improving Scenario Methods in Infrastructure Planning: A Case Study of Long Distance Travel and Mobility in the UK Under Extreme Weather Uncertainty and a Changing Climate", Technological Forecasting and Social Change, 115: 180-197. Doi: 10.1016/J.Techfore.2016.10.002

Zhang, X.-B., Sun, J., Fei, Y. and Wei, C. (2020) "Cooler Rooms on a Hotter Planet? Household Coping Strategies, Climate Change, and Air Conditioning Usage in Rural China", Energy Research & Social Science, 68: 101605. Doi: 10.1016/J.Erss.2020.101605

Zhang, S., Guo, Q., Smyth, R. and Yao, Y. (2022) "Extreme Temperatures and Residential Electricity Consumption: Evidence from Chinese Households", Energy Economics, 107: 105890. Doi: 10.1016/J.Eneco.2022.105890

Zhao Et Al. (2021) "Global, Regional, And National Burden of Mortality Associated with Non-Optimal Ambient Temperatures From 2000 To 2019: A Three-Stage Modelling Study", The Lancet Planetary Health, 5(7): E415-E425.

Appendix 1. Population and GDP per capita of every city for each region



We identify cities which are on the Population-GDP per Capita Frontier. İzmir for the Aegean region, Samsun for the Black Sea region, Ankara, Kayseri, Konya for the Central Anatolia, İstanbul, Bursa, Kocaeli and Tekirdağ for the Marmara region, Adana, Antalya, Hatay, Mersin for the Mediterranean region, Diyarbakır, Gaziantep, Şanlıurfa for the Southeast Anatolia. Due restrictions of the Nielsen data Tekirdağ is replaced with Eskişehir and Hatay with Kahramanmaraş which are similar in terms of regional climate, population density and purchasing power.

Appendix 2. Panel Cointegration Tests

Pedroni test for Cointegration	Average temperature	Maximum temperature	Number of days above 30ºC	Extreme heat 1	Extreme heat 2
Modified Phillips–Perron	2.8088***	2.6393***	2.1699**	2.6518***	2.6893***
Phillips–Perron t	-6.0451***	-5.6869***	-5.9149***	-5.5337***	-5.1276***
Augmented DF t	-4.3499***	-4.1895***	-3.6428***	-5.4998***	-4.9302***
*** p<0.01, ** p<0.05, * p<0.1					
H_0: No cointegration			H_a: All panels are cointegrated		

Note: Pedroni (1999, 2004)) is reported in Appendix A2 for the cointegration relationships of the variables; demand (perctAC), respective extreme weather variable (avgtemp, maxtemp, over30Cdays, DegreesOAvg, Wover30Cdays), log gross national product (loggdpc) and log city population (logpop).

Westerlund (2005) tests of cointegration are based on the variance ratio and in all the specs used for the Kao and Pedroni tests, the cointegration relationship is accepted at least at 5% level for the Westerlund tests also.

KATKI ORANI / *CONTRIBUTION RATE*	**AÇIKLAMA / *EXPLANATION***	**KATKIDA BULUNANLAR / *CONTRIBUTORS***
Fikir veya Kavram / *Idea or Notion*	Araştırma hipotezini veya fikrini oluşturmak / *Form the research hypothesis or idea*	Mehmet Ali SOYTAŞ Asst. Prof. Damla DURAK UŞAR (Ph.D.)
Tasarım / *Design*	Yöntemi, ölçeği ve deseni tasarlamak / *Designing method, scale and pattern*	Mehmet Ali SOYTAŞ Asst. Prof. Damla DURAK UŞAR (Ph.D.)
Veri Toplama ve İşleme / *Data Collecting and Processing*	Verileri toplamak, düzenlenmek ve raporlamak / *Collecting, organizing and reporting data*	Mehmet Ali SOYTAŞ Asst. Prof. Damla DURAK UŞAR (Ph.D.)
Tartışma ve Yorum / *Discussion and Interpretation*	Bulguların değerlendirilmesinde ve sonuçlandırılmasında sorumluluk almak / *Taking responsibility in evaluating and finalizing the findings*	Mehmet Ali SOYTAŞ Asst. Prof. Damla DURAK UŞAR (Ph.D.)
Literatür Taraması / *Literature Review*	Çalışma için gerekli literatürü taramak / *Review the literature required for the study*	Mehmet Ali SOYTAŞ Asst. Prof. Damla DURAK UŞAR (Ph.D.)

Hakem Değerlendirmesi: Dış bağımsız.

Çıkar Çatışması: Yazar çıkar çatışması bildirmemiştir.

Finansal Destek: Yazar bu çalışma için finansal destek almadığını beyan etmiştir.

Teşekkür: -

Peer-review: Externally peer-reviewed.

Conflict of Interest: The author has no conflict of interest to declare.

Grant Support: The author declared that this study has received no financial support.

Acknowledgement: -