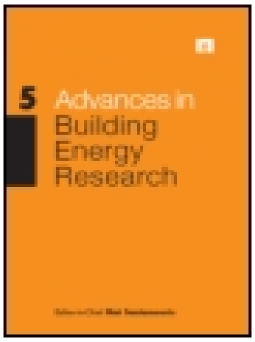

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An analysis of indoor temperature measurements in low- and very-low-income housing in Athens, Greece

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Fuel poverty is a complex socioeconomic problem that affects low-income households and has a serious impact on indoor environmental quality. In this research, indoor temperatures were measured in 50 low- and very-low-income dwellings in the major Athens area in Greece during the winter of 2012–2013. Initially, *k*-means clustering was employed to group the households into three clusters (Poorest, Average and Richest) based on mean indoor temperature, surface area of the dwelling, number of rooms, family size, building age and income; 7.6% of the households of the Richest Cluster, 8.6% of the Average Cluster and 11.6% of the Poorest Cluster were fuel poor and indoor temperatures were much below accepted standards. Separate Hildreth-Lu AR(1) regressions with robust standard errors, estimated for the indoor temperature measurements of the 50 households, showed that these families were able to exercise only a limited amount of control in heating their homes. Finally, ordinary least squares regressions with Arellano robust standard errors, estimated on the pooled temperature measurements of all households, confirmed that families in the Richest and Average Clusters were better off than those in the Poorest Cluster and showed that fuel poverty motivated people to use alternative heating sources with some success.

Keywords: indoor temperature; low-income households; fuel poverty; energy consumption; time series; panel data

Introduction

Achieving proper indoor temperatures in buildings is necessary to protect human health, satisfy thermal comfort and improve quality of life. Very low or very high indoor temperatures have been found to increase seasonal morbidity and mortality and constrain the social attainment of households (Bouzarovski, 2011). Unfortunately, about 15–25% of the low-income population in Southern Europe and Ireland cannot afford to pay for heating (Böhnke, 2003), with these figures likely to have increased dramatically because of the worsening economic conditions.

Fuel poverty, the inability to afford adequate warmth at home, is one of the most prominent social problems of the twenty-first century (Boardman, 1991, 2010), particularly in these times of global economic recession. It affects low-income families and its causes lie in the poor quality of the housing stock and the high cost of fuel. This paper documents the analysis of temperature measurements and socioeconomic data of low- and very-low-income households in order to

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discover how such families can be clustered into groups and to understand the variation in the indoor temperatures of their homes. The rest of the paper is structured into a literature review, methodology, results and conclusions.

Literature review

Poverty and fuel poverty are linked but not synonymous concepts (Boardman, 1991). Fuel-poor households include low-income households, vulnerable households and households with high energy bills and payment difficulties (Hill, 2012). Vulnerable households contain children, elderly people and persons who are disabled or suffer from long-term illnesses (Boardman, 2010; Hill, 2012). Oftentimes, fuel-poor people are those who receive social security payments, work on a part-time basis or are in debt. Unemployment and growing job insecurity (part-time employment, short-term jobs) are causing a lot of people to live below the poverty threshold (Department of Energy and Climate Change [DECC], 2012).

Fuel poverty is measured by the fuel poverty ratio (FPR), which is defined as

$$\text{FPR} = \frac{\text{Energy consumption} \times \text{Price}}{\text{Income}}. \tag{1}$$

If the FPR is greater than 0.1 (10%), the household is considered to be fuel poor (DECC, 2012; Department of Trade and Industry, 2001). Fuel poverty is a complex socio-technical problem caused by a combination of physical, demographic and behavioural characteristics of a household (Kelly, 2011). Factors that have been found to drive residential energy consumption include: number of household occupants (very strong influence), household income (very strong correlation), building type, construction age, floor area, household heating patterns and living room temperature (Braun, 2010; Department of the Environment, 1996; EU Fuel Poverty Network, 2012; Santamouris et al., 2007; Whyley & Callender, 1997).

Santamouris et al. (2014) reviewed several national and international standards that define the threshold indoor temperatures required to maintain comfortable conditions in buildings (Chartered Institution of Building Services Engineers, 2009; Comite Normalisation, 2007; International Standards Organisation, 2005). Proposed indoor temperatures are between 18°C and 21°C, varying as a function of many parameters regulating thermal comfort. The World Health Organization (World Health Organization [WHO], 2009) proposes 20°C for the vulnerable population, while 18°C is proposed by Boardman (1991). Various medical sources propose 21°C as a minimum temperature for the more vulnerable population and 18°C for sedentary activities and people in good health (Healy & Clinch, 2002), while the WHO proposes minimum temperatures of 16°C in bedrooms and 18°C in living rooms for health reasons.

Most of the existing data on cold homes are available from the UK, Ireland and other northern countries, where several studies have been carried out and many policies applied to improve the problem. As mentioned by Santamouris et al. (2014), most of the experimental studies carried out in Northern Europe and the UK have found that indoor temperatures in low-income houses are low and often inadequate for human comfort, with problems of internal condensation, mould and dampness found in elevated parts of buildings (Burholt & Windle, 2006; Critchley, Gilbertson, Grimsley, & Green, 2007; Holgersson & Norlen, 1984; Hong et al., 2009; Hunt & Gidman, 1982; Hutchinson, Wilkinson, Hong, Oreszczyn, & the Warm Front Study Group, 2006; Kavgic et al., 2012; Oreszczyn, Hong, Ridley, & Wilkinson, 2006; Short & Rugkasa, 2007; Summerfield et al., 2007; Yohanis & Mondol, 2010; Zavadskas, Raslanas, & Kaklauskas, 2008). In some cases, very low temperatures have been found, which put the health of human beings at risk (Böhnke, 2003).

Fuel poverty in Greece is a serious problem. Healy and Clinch (2002) estimated fuel poverty in the country to vary between 24.6% and 36%. Based on the criteria proposed by Bouzarovski (2011), the percentage of fuel poverty in Greece is close to 36%, while according to Thomson and Snell (2013) it is between 16% and 17%. Eurostat (2012) mentions that almost 20% of the population lives in low-income housing, while Böhnke (2003) reports that almost 28% of the population lives in houses with leaking windows; it is also reported that 26% of the low-income population in Greece cannot afford to pay for heating, with the national average being close to 8%.

Various fuel poverty studies have classified low-income households into groups. For example, four types of households have been identified in Austria (the 'overcharged', the 'modest fuel poor', the 'modest non-fuel poor' and those 'on a low income') (Brunner, Spitzer, & Christanell, 2011) with similar results obtained in France (Devaliere, 2010). Santamouris et al. (2013) collected and analysed energy consumption data for 598 households in Greece for the winters of 2010–2011 and 2011–2012. Although the latter winter was harsher, households consumed 37% less energy than expected. Cluster analysis rendered two clusters: three-quarters of the households belonged to the lower-income group that lived in smaller spaces, had half the income and consumed more specific energy compared to the high-income group (although much less than expected based on the degree-hours of the second winter). One out of three higher-income and one out of four lower-income households adopted some conservation measures after the first winter, while 2% of the higher-income and 14% of the lower-income households were below the fuel poverty threshold.

In a later study focusing on 50 low- and very-low-income dwellings in Athens, Santamouris et al. (2014) measured indoor temperatures and collected energy, environmental, social and health-related data during the winter of 2012–2013. Data were grouped in five clusters based on indoor temperature characteristics. Indoor temperatures were found to be much below the accepted standards, often putting the health and even the survival of the residents at risk. The energy consumption for heating was found to be much below the country's threshold, with a high fraction of households not using heating energy at all.

Based on this review of the pertinent published literature, it is concluded that investigating fuel poverty and indoor temperatures in Greece is a worthwhile research endeavour. Attention now shifts to specific research questions and the appropriate methodology with which to address them.

Methodology

The following questions are addressed in this research:

(1) Which social, economic and physical/infrastructure variables are influential in grouping low- and very-low-income households into homogeneous clusters? How many such clusters are formed, that is, what is the best clustering scheme? Do these clusters correspond to social/income classes? How do they compare to previous research in the area? How do the clusters compare with one another, especially in terms of available living space, employment status, income, household insulation, energy consumption and fuel poverty?

(2) How do the measured indoor temperatures vary per month, day of the week, hour, household and cluster? How may the temperature time series be modelled as a function of time, season and the socioeconomic characteristics of the household?

Empirical data were used to answer the above research questions. As described by Santamouris et al. (2014), miniature temperature sensors were placed in 50 low- and very-low-income homes in

Athens, Greece. Almost all of the selected houses were located in dense inner-city areas characterized by social, economic and environmental problems (Livada, Santamouris, Niachou, Papanikolaou, & Mihalakakou, 2002). Sensors (accurate to 0.5°C or better) were placed in a well-ventilated and heat-protected part of the house and were properly calibrated. Measurements were carried out from December 2012 or later to April 2013, collected by trained surveyors and inspected for spurious measurements or other evident problems.

To address the first research question, it was decided that, since the temperature measurement started at different times for each household, cluster analysis should be estimated on a subsample restricted to the time period of 5 March to 15 April 2013, for which temperature measurements were available for all 50 dwellings. The full sample period was used to respond to the second research question. Initially, 50 separate temperature time series regressions were estimated, one for each household; subsequently, a few alternative pooled regression models were estimated corresponding to the unbalanced panel data structure of the 50 households (each with its own temperature time series).

Minitab version 17.1.0 and Gretl version 1.9.90 (Baiocchi & Distaso, 2003) were used for graphing and econometric analysis.

Results

The results commence with descriptive statistics and graphs of key variables of the 50 households, continue with *k*-means clustering that groups the households into homogeneous clusters, and are completed with appropriate time series and panel data regression models for analysing the indoor temperature time series.

Descriptive analysis

Minimum, average and maximum temperatures per household and month are tabulated in Table 1. The leftmost column lists labels for the 50 households and the one next to it shows overall average, minimum and maximum (the last two in parentheses) values for the entire duration of the study; of these, the lowest indoor temperatures recorded in the households, T34BALAT (5°C), T35SFYR (5.6°C) and T18XEST (5.8°C), underscore the extremely uncomfortable thermal conditions prevailing in some low-income homes. As expected, December (minimum of 8.9°C for all 50 households), January (5°C) and February (7.7°C) were the most difficult months for most households, with an average temperature of around 11–12°C for the most thermally challenged homes. These values compare very poorly with the sufficient standard of warmth, usually identified as 21°C for the main living area and 18°C for other rooms (WHO, 1987). The distribution of average household temperatures is plotted in the histogram of Figure 1 and suggests the presence of three clusters in the sample (Everitt, Landau, Leese, & Stahl, 2011).

Of the 50 households polled, 43 were apartments (86%) and seven detached houses (14%). Their surface areas varied from 20 to 170 m², with an average value of 75.6 and 51.1 m² corresponding to each household member for each household type. A histogram of the surface areas is shown in Figure 2 and suggests three (or more) clusters, including one that would be big. Families dwelling in the detached houses (as opposed to apartments) had a minimum of one and a maximum of four members, with single-member families representing about half of the homes (52%); the average family had 1.6 members. About one in five (22%) of the people interviewed were unemployed and one in four (24%) pensioners.

The 50 houses had one to five rooms, with 19 (38%) houses having three rooms, as depicted in the bar chart of Figure 3. The surface area of each room varied from 15 to 60 m², with an average value of 33.9 m². This meant that was an average of 1.7 rooms per household member, although

Table 1. Temperature average (minimum, maximum).

Label	Overall	December 2012	January 2013	February 2013	March 2013	April 2013
Overall	17.1 (5.0, 28.6)	15.8 (8.9, 23.9)	15.8 (5.0, 24.4)	16.2 (7.7, 25.3)	17.3 (9.4, 28.6)	19.8 (14.9, 26.1)
T01AMAL	17.2 (11.8, 23.9)	15.3 (13.6, 17.4)	15.7 (11.8, 20.4)	16.4 (13.2, 23.0)	18.3 (15.3, 21.5)	21.3 (19.3, 23.9)
T02GRIG	18.5 (14.8, 22.2)			16.5 (14.8, 18.6)	18.6 (16.4, 20.7)	21.1 (20.3, 22.2)
T03DEMER	17.3 (15.0, 20.6)	16.9 (15, 19.6)	16.8 (15.0, 19.2)	16.6 (15.4, 18.3)	17.5 (16.1, 19.3)	19.8 (18.7, 20.6)
T04DIAL	17.9 (15.1, 21.9)	16.8 (15.9, 17.9)	17.1 (15.6, 18.2)	17.5 (15.1, 19.0)	18.3 (16.4, 20.8)	20.7 (19.9, 21.9)
T05IOANK	17.0 (14.1, 21.2)	16.2 (15.2, 20.8)	16.1 (14.1, 20.1)	16.4 (15.2, 18.4)	17.4 (15.5, 19.4)	19.9 (19.2, 21.2)
T06IOANL	17.0 (14.3, 21.2)	16.3 (14.7, 19.5)	16.5 (14.4, 19.0)	16.5 (14.3, 19.4)	17.3 (15.3, 19.1)	19.5 (18.3, 21.2)
T07KARR	13.7 (9.1, 19.3)	12.5 (11, 14.2)	11.8 (9.1, 13.6)	12.8 (11.3, 15.0)	14.9 (12.9, 17.5)	18.3 (17.3, 19.3)
T08KONT	17.0 (11.4, 24.1)	15.1 (13.5, 17.3)	14.9 (11.4, 17.5)	16.3 (14.5, 18.8)	18.3 (15.6, 21.4)	21.9 (19.6, 24.1)
T09LAGOUT	17.2 (13.3, 22.7)			15.4 (13.3, 19.7)	17.3 (14.5, 22.7)	19.7 (18.1, 22.4)
T10LYBER	16.8 (11.5, 21.3)	16.2 (14.8, 20.5)	15.9 (13.5, 17.6)	15.9 (11.5, 17.8)	17.3 (15.8, 19.1)	19.6 (18.5, 21.3)
T11DESP	16.4 (11.0, 20.8)	16 (14.1, 19.2)	15.0 (11.0, 17.3)	15.6 (13.8, 17.6)	16.9 (14.0, 19.7)	19.9 (18.6, 20.8)
T12BREH	17.2 (10.5, 25.3)	18.6 (16.3, 20.6)	17.5 (13.8, 20.0)	15.5 (10.5, 25.3)	16.7 (11.6, 24.6)	19.0 (18.0, 20.3)
T13MOLG	17.6 (13.5, 23.2)	17.9 (15, 22.5)	17.1 (13.5, 23.2)	17.2 (14.8, 18.5)	17.7 (14.5, 19.5)	19.1 (18.4, 19.9)
T14STAVR	16.8 (12.2, 20.0)	15.5 (14.1, 17.6)	15.7 (12.2, 18.5)	16.7 (14.6, 18.5)	17.4 (15.4, 18.7)	19.2 (18.0, 20.0)
T15TOUR	15.7 (9.4, 23.7)	14 (10.8, 18.7)	14.5 (9.4, 18.5)	15.3 (11.8, 19.3)	16.5 (12.1, 21.0)	18.8 (16.2, 23.7)
T16KARA	15.8 (10.9, 21.6)	15.2 (13.9, 17.2)	14.6 (10.9, 16.7)	15.4 (13.6, 18.0)	16.2 (13.8, 19.6)	18.9 (17.2, 21.6)
T17SPAN	17.1 (11.6, 20.3)	16.2 (14.1, 20.3)	16.3 (11.6, 18.9)	17.4 (14.2, 18.8)	17.3 (15.9, 18.9)	18.7 (17.8, 19.6)
T18XEST	15.6 (5.8, 23.9)	13.7 (10.7, 23.9)	13.2 (5.8, 18.1)	15.8 (14.3, 17.6)	17.0 (15.2, 18.7)	19.2 (18.2, 20.2)
T19MOLV	16.6 (11.0, 20.7)	16.4 (13.3, 19)	15.8 (11.0, 18.6)	15.7 (14.0, 20.7)	16.7 (14.3, 19.4)	19.5 (17.8, 20.5)
T20RAPT	17.0 (13.7, 20.2)			16.0 (13.7, 18.2)	16.7 (14.8, 18.5)	19.0 (18.0, 20.2)
T21MAZA	19.3 (13.3, 25.3)	18.2 (15.7, 22)	18.2 (13.3, 22.6)	18.9 (15.0, 23.6)	19.8 (16.5, 23.0)	22.1 (19.3, 25.3)
T22ZEK	17.5 (10.3, 24.4)	16.9 (12.5, 21)	16.5 (10.3, 24.4)	16.6 (11.8, 22.6)	18.3 (12.1, 24.4)	19.8 (16.7, 24.2)
T23LAFAZ	18.7 (15.0, 23.4)	18 (16, 20.6)	18.5 (15.2, 21.9)	19.3 (16.3, 23.4)	18.0 (15.0, 20.9)	19.8 (18.1, 22.1)
T24MAZH	19.1 (14.0, 25.9)	17.8 (14.7, 22.2)	18.3 (14.0, 22.8)	18.6 (14.9, 23.3)	19.5 (15.6, 22.9)	21.9 (18.5, 25.9)
T25KAPS	18.2 (11.4, 28.6)				17.0 (11.4, 28.6)	20.6 (14.9, 26.1)
T26TZOG	17.8 (13.5, 21.6)				17.2 (13.5, 21.6)	19.1 (17.1, 21.5)
T27MAVR	20.2 (15.8, 26.7)				19.5 (15.8, 26.7)	21.4 (19.2, 25.0)
T28KAKAB	16.7 (10.7, 21.9)				15.4 (10.7, 19.6)	19.1 (16.6, 21.9)
T29TASS	19.2 (16.4, 23.0)				18.8 (16.4, 23.0)	20.0 (17.0, 22.8)
T30SABIOL	15.8 (11.5, 19.8)				14.8 (11.5, 18.0)	17.8 (16.1, 19.8)
T31GERON	16.8 (13.7, 20.8)	18.0 (13.8, 19.6)	16.4 (13.7, 18.6)	16.4 (13.8, 18.7)	16.1 (13.9, 19.1)	19.5 (17.9, 20.8)
T32KAIM	16.5 (12.9, 20.9)	16.7 (15.1, 18.6)	15.8 (12.9, 19.0)	15.7 (14.0, 17.6)	16.6 (14.2, 18.9)	19.2 (18.4, 20.9)

(*Continued*)

Table 1. Continued.

Label	Overall	December 2012	January 2013	February 2013	March 2013	April 2013
T33DIAM	16.9 (14.2, 23.2)	16.6 (14.6, 22.9)	16.9 (14.2, 23.2)	16.2 (14.5, 17.7)	16.6 (15.0, 18.7)	18.9 (18.2, 20.4)
T34BALAT	13.4 (5.0, 21.8)	11.7 (8.9, 14.9)	11.4 (5.0, 15.5)	12.5 (7.7, 16.7)	14.6 (9.4, 19.7)	18.7 (15.8, 21.8)
T35SFYR	13.3 (5.6, 19.9)	11.5 (8.9, 13.9)	11.4 (5.6, 14.5)	12.6 (9.4, 15.4)	14.4 (10.9, 18.1)	17.9 (16.5, 19.9)
T36PAPA	17.0 (13.4, 20.3)	16.3 (15.0, 17.4)	15.9 (13.4, 17.6)	16.5 (15.0, 18.0)	17.6 (15.9, 19.1)	19.4 (18.7, 20.3)
T37DRET	17.1 (14.3, 24.2)	17.2 (15.9, 18.3)	16.4 (14.3, 17.7)	15.8 (14.3, 17.7)	17.4 (15.3, 20.2)	19.8 (19.1, 24.2)
T38STERG	16.4 (10.5, 23.3)	15.4 (12.8, 19.3)	15.0 (10.5, 18.1)	15.6 (12.2, 18.7)	17.1 (13.9, 21.3)	20.5 (18.0, 23.3)
T39KOUV	17.9 (14.9, 21.4)	17.0 (14.9, 19.2)	17.6 (15.4, 20.3)	17.0 (14.9, 19.2)	18.2 (16.2, 20.2)	20.4 (19.7, 21.4)
T40PSIS	17.6 (13.7, 22.9)			15.9 (13.7, 19.3)	17.4 (14.5, 20.9)	20.1 (18.2, 22.9)
T41VOITS	17.3 (13.6, 22.6)	15.0 (14.3, 16.2)	16.4 (14.1, 19.7)	16.4 (13.6, 22.0)	18.0 (14.2, 20.2)	20.7 (19.8, 22.6)
T42ALEV	17.3 (12.8, 21.9)	13.8 (13.0, 17.8)	15.5 (12.8, 18.1)	17.6 (15.5, 20.0)	18.2 (16.1, 20.6)	20.7 (19.5, 21.9)
T43MANOU	17.4 (13.0, 23.3)	15.1 (13.6, 18.4)	16.6 (13.0, 21.4)	17.1 (14.3, 22.0)	17.9 (15.4, 21.1)	20.4 (18.7, 23.3)
T44TSIT	17.7 (12.7, 21.8)	16.7 (14.7, 18.4)	16.9 (14.0, 19.2)	16.7 (12.7, 19.6)	18.5 (15.3, 20.8)	20.4 (19.7, 21.8)
T45MOURT	17.7 (14.0, 20.4)	16.8 (16.1, 17.4)	16.8 (14.0, 19.4)	17.4 (16.3, 18.7)	18.1 (16.9, 19.6)	19.6 (18.9, 20.4)
T46SOTIR	17.3 (12.8, 23.7)	15.3 (12.8, 19.5)	16.3 (14.3, 19.3)	16.2 (13.8, 20.0)	18.3 (14.3, 21.5)	20.9 (19.4, 23.7)
T47ARVAN	16.7 (11.1, 22.1)	13.6 (11.8, 16.6)	15.0 (11.1, 19.4)	16.2 (13.9, 19.4)	18.0 (14.8, 21.2)	20.9 (19.3, 22.1)
T48TSIG	17.2 (13.7, 21.2)			15.3 (13.7, 18.0)	16.7 (14.1, 21.1)	19.4 (18.0, 21.2)
T49SVOUR	17.6 (14.3, 22.3)			15.5 (14.3, 17.1)	17.1 (14.9, 22.3)	19.7 (18.1, 21.7)
T50HARIT	18.0 (14.9, 22.0)			17.1 (15.4, 19.0)	17.3 (14.9, 19.7)	19.8 (18.4, 22.0)

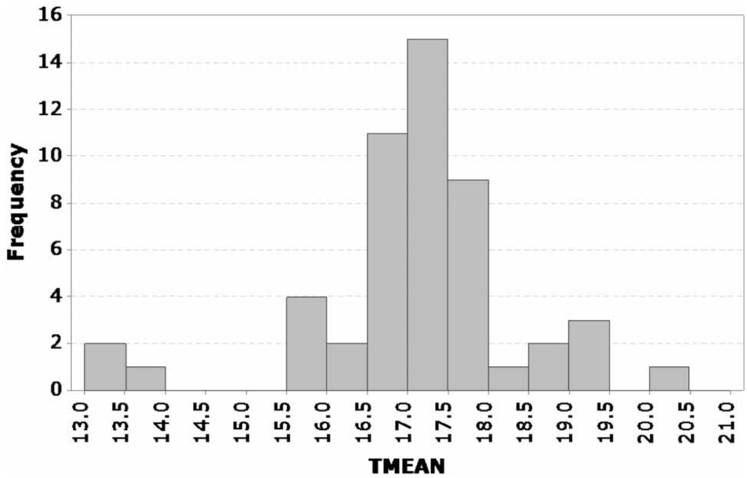

Figure 1. Histogram of indoor temperatures (in degrees centigrade).

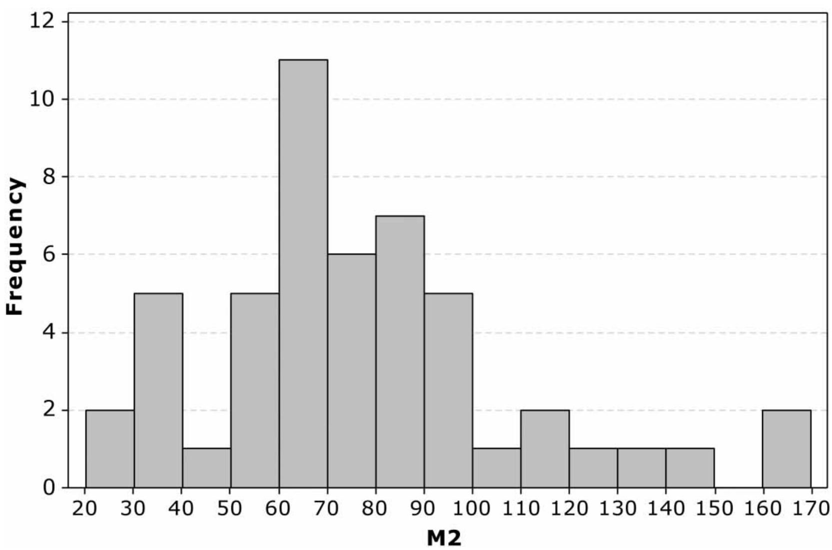

Figure 2. Histogram of surface area (in square metres).

there were some crowded households with one room per two members. Although not shown, the histogram of square metres per family member also indicated the presence of an imposing cluster (possibly split into two sub-clusters) and (at least) one smaller cluster.

Building age varied from 2 to 78 years with an average value of 29.3 years. Its histogram, depicted in Figure 4, shows the same two spurts of building activity present in Santamouris et al. (2013) and thus indicates the presence of two large clusters along with a smaller one.

Average household income fell from 8867 euros in 2011 to 8087 euros in 2012, with a typical household losing 787 euros (a decrease of 8.9%). Average income per member equalled 5873 euros. The distribution of income is shown in Figure 5.

Half of the houses were insulated and slightly more than half (54%) had double-glazed windows. Cross-tabulation showed that most dwellings were both insulated and double-glazed.

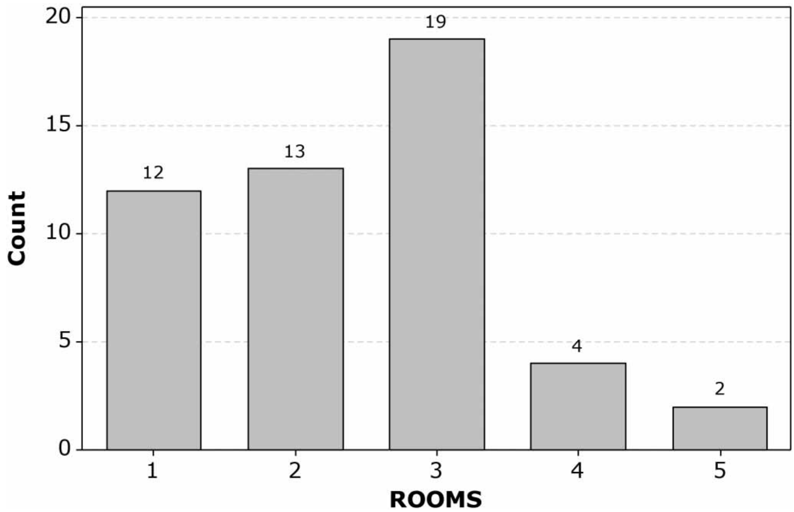

Figure 3. Bar chart of the number of rooms in the houses.

84% of the houses had some form of heating and 65.12% used autonomous heating systems. As to the heating source, 78% of households used oil and only 4% natural gas. Air conditioning was used in 42% of the houses. Most dwellings declared that some other means of heating were also used, including electric radiators (12% of cases), fan heaters (8%), stoves (8%), electric stoves and fireplaces. Central heating was used in 45.8% of the households in 2011, a percentage that fell to 34.7% in 2012, underlining the effects of the deepening economic recession.

The monthly electricity charge for households varied from zero (i.e. no electricity consumed) to 110 euros with an average of 56.1 euros. Its histogram, shown in Figure 6, is characterized by multimodality that suggests the presence of three or four clusters in the sample. In response to the

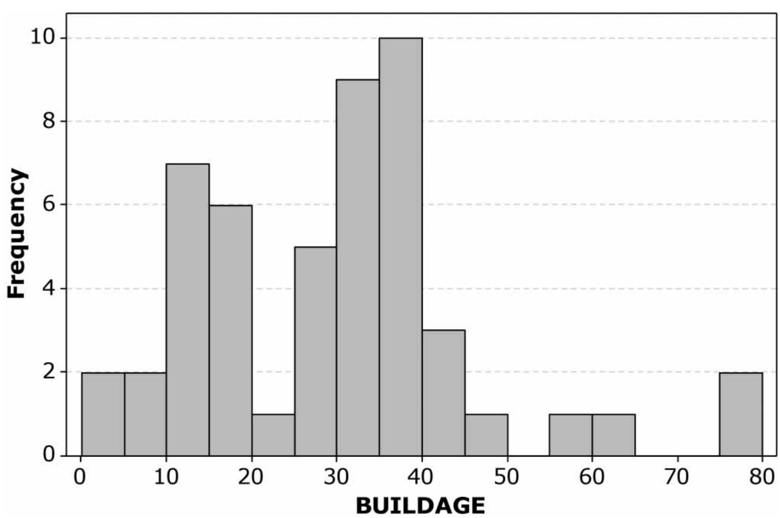

Figure 4. Histogram of building age (in years).

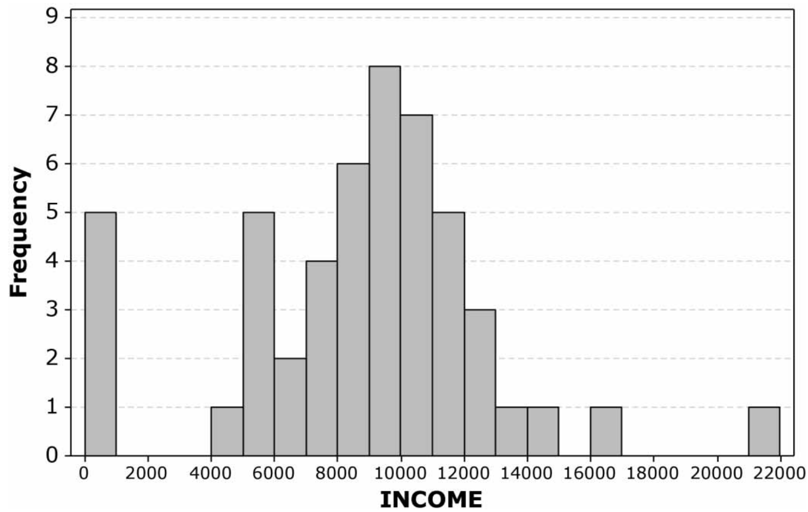

Figure 5. Histogram of household income (in euros).

worsening economic conditions, oil consumption fell from 110.9 litres in 2011 to 52.2 litres (a reduction of 52.9%) in 2012.

Electricity charges were added to the oil cost so that total energy costs could be estimated (excluding the cost of non-electric means such as fireplaces or wood stoves). Such energy costs for the year 2012 averaged at 730.7 euros, varying from zero to 1454 euros. The average value of the FPR for the sample was 8.4% with a maximum of 18.9%. Since neither the cost of non-electric heating sources nor the cost of other energy consumption activities (such as water heating, lights, appliances and cooking) was included in the computation of the FPR, the values presented here are lower bounds for its true values. A histogram of the FPR is depicted in Figure 7 and shows likely multimodality and the presence of three potential clusters.

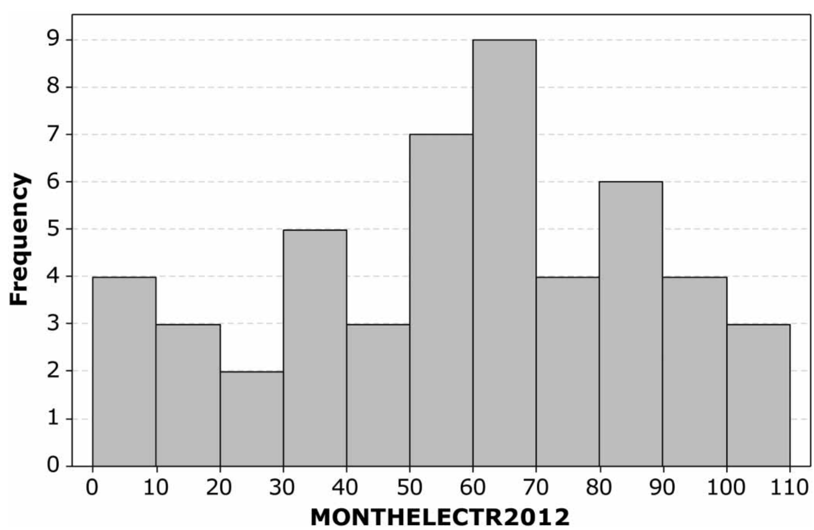

Figure 6. Histogram of monthly electricity charge (in euros).

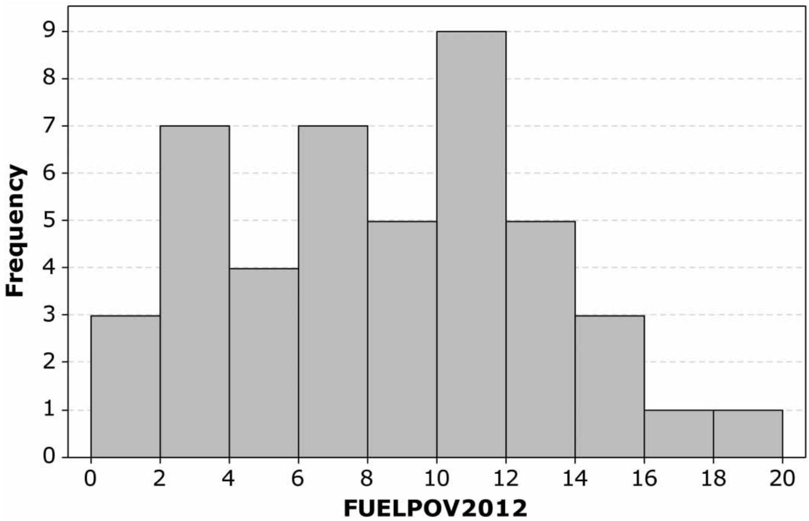

Figure 7. Histogram of FPR (as a percentage).

The graphical and numerical descriptive analysis of the 50 households having been completed, attention now shifts to discovering household clusters.

Cluster analysis

Santamouris et al. (2013) used the following variables for clustering a similar set of households: income, annual income change, number of family members, building age, surface area, use of oil or gas, and annual energy consumption change. In the newer study by the same research group (Santamouris et al., 2014), a similar set of low- and very-low-income households was grouped into five clusters based on qualitative criteria and the following variables: average indoor temperature, minimum and maximum indoor temperature, age, professional status (students, employed), average annual income, detached house or apartment, cost of fuel, cost of electricity, central heating and air conditioning.

A rigorous approach is adopted as regards the issue of sample size. Formann (1984), as quoted by Mooi and Sarstedt (2011), recommends a sample of at least 2^m cases, where m equals the number of clustering variables. With 50 cases, this equals:

$$2m = n \Rightarrow m = \frac{\log(n)}{\log(2)} = \frac{\log(50)}{\log(2)} = 5.64. \quad (2)$$

In other words, it is recommended that this research employs no more than 5–6 variables in the cluster analysis. Given this restriction, it was decided that the following key variables should be used: average indoor temperature in °C (TMEAN3), surface area in m² (M2), number of rooms (ROOMS), number of household members (MEMBERS), building age (BUILDAGE) and average annual income in euros (INCOME). The reader is reminded that clustering was estimated on a subsample, restricted to the time period from 5 March to 15 April 2013, for which indoor temperature measurements were available for all 50 dwellings.

Since all clustering variables were quantitative, *k*-means clustering with Euclidean distance (Garson, 2012) and standardized data was run. There is a wide array of different clustering algorithms (Everitt et al., 2011; Milligan & Cooper, 1985). A practical distinction is the differentiation between hierarchical and partitioning methods (most notable of which is the *k*-means optimization procedure). The *k*-means algorithm, one of the simplest and most popular non-hierarchical methods, follows an entirely different concept than hierarchical clustering methods (Mooi & Sarstedt, 2011): it does not rely on distance measures (although Euclidean distances are estimated and used by the algorithm) to formulate clusters but chooses them so that within-cluster variation is minimized, in this sense being more robust than hierarchical methods. Finally, *k*-means has been reported as being superior to hierarchical clustering methods as it is less affected by outliers and the presence of irrelevant clustering variables (Mooi & Sarstedt, 2011).

Given these considerations and the previous success of the authors with the use of the method in a similar analysis (Santamouris et al., 2014), *k*-means clustering was chosen for this research. The most important issue associated with the application of *k*-means, that is, that the researcher has to pre-specify the number of clusters to be extracted from the data, was in fact not a problem since two-, three-, four- and five-cluster solutions were estimated and appropriate statistical tests (ANOVA or chi-square) were run to assess how different the cluster centroids were. Based on this analysis, it was decided that the three-cluster solution represented the optimal clustering of this data set: Cluster 1 had 20 members (40% of the sample), Cluster 2 had 21 members (42%) and Cluster 3 had 9 members (18%). It can be seen that the three clusters formed include two larger ones (Clusters 1 and 2) and a smaller one (Cluster 3). The nature of each cluster may be understood by examining the values of variables at the cluster centroids (shown in Table 2).

Beginning the interpretation of the three clusters with the INCOME variable, it may be observed that Cluster 3 (hereafter labelled ‘Poorest’) contained the lowest-income and Cluster 1 (‘Richest’) the highest-income households, with Cluster 2 (‘Average’) having intermediate income values, the difference among cluster centroid income values being highly significant ($E = 0.000$). The Poorest Cluster (3) had the smallest families and occupied the smallest surface area with the fewest rooms, while the Richest Cluster (1) had the biggest families and occupied the largest surface area with the most rooms. As expected, the Poorest Cluster lived in the oldest buildings and had the lowest average indoor temperature.

A better understanding of the nature of the three clusters may be gained by looking at the values of the other variables at the cluster centroids (shown in Table 3). To start with, the indoor temperature range of all clusters (especially the Poorest) was well below 21°C. More than half of the residents in the Poorest Cluster were unemployed, compared to a quarter in the Average Cluster and only 5% in the Richest Cluster. On the other hand, 40% of the residents in the Richest Cluster were pensioners. Space per household member was about 50–51 m² and that per room around 30–36 m² for all three clusters, with more rooms per household member in the Richest Cluster. Income change for the two-year period was greatest for the Richest Cluster but income per household member was only 1856 euros in the Poorest Cluster, compared

Table 2. Cluster centroids for clustering variables.

Clustering variable	Cluster 1 ‘Richest’ ($n = 20$)	Cluster 2 ‘Average’ ($n = 21$)	Cluster 3 ‘Poorest’ ($n = 9$)	ANOVA p-value
TMEAN3	18.663	18.273	17.813	0.123
M2	88.20	69.81	61.22	0.072
ROOMS	3.05	2.0952	1.7778	0.001
MEMBERS	1.9000	1.5238	1.3333	0.127
BUILDAGE	34.00	21.36	37.33	0.014
INCOME	11,850	7936	2133	0.000

Table 3. Cluster centroids or percentages for other variables.

Other variable	Cluster 1 'Richest' ($n = 20$)	Cluster 2 'Average' ($n = 21$)	Cluster 3 'Poorest' ($n = 9$)	ANOVA or chi-square p-value
Minimum temperature	14.780	14.824	13.561	0.130
Maximum temperature	22.500	21.776	21.600	0.375
Temperature range	6.220	6.000	5.817	0.902
Unemployed	5%	23.81%	55.56%	0.009
Pensioner	40%	14.29%	11.11%	0.095
Apartment	90%	85.71%	77.78%	0.680
m² per member	51.42	51.25	50.11	0.991
m² per room	30.28	36.59	35.91	0.272
Rooms per member	1.9292	1.5397	1.5000	0.374
2011 income	12,450	8253	2133	0.000
2012 income	11,250	7626	2133	0.000
Income change	−9.43	−5.58	0.00	0.379
Income per member	7835	6011	1856	0.000
Income per m²	176.41	124.80	51.32	0.003
Insulation	40%	71.43%	22.22%	0.024
Double-glazed windows	40%	76.19%	33.33%	0.026
Autonomy	68.75%	78.95%	25%	0.025
Oil	90%	71.43%	66.67%	0.237
Air conditioning	45%	42.86%	33.33%	0.836
2011 central heating	52.63%	40.00%	44.44%	0.728
2012 central heating	47.37%	28.57%	22.22%	0.315
2012 monthly electricity charge	64.53	52.39	45.80	0.176
2012 monthly electricity charge per m²	0.8136	0.7842	0.6631	0.680
2012 monthly electricity charge per room	23.55	29.24	28.01	0.606
2011 oil consumption (litres)	120.2	109	95.5	0.921
2012 oil consumption (litres)	90.04	32.75	17.95	0.064
Oil consumption change	−28.6	−71.0	−77.6	0.391
2012 energy cost	864.0	671.3	572.9	0.119
2012 energy cost per m²	11.257	9.950	8.325	0.547
2012 FPR (%)	7.601	8.555	11.599	0.267

to just over 6000 in the Average and almost 8000 in the Richest Cluster. Interestingly, more homes in the Average Cluster were insulated and double-glazed than in the other two.

Turning to energy, heating autonomy was available in many more households of the Richest and Average Clusters (over two-thirds) than the Poorest Cluster (one quarter). Also, air conditioning was used by one-third of the households in the Poorest Cluster, compared to over 40% in the other two. Comparing central heating in 2011 and 2012, it can be seen that its use by the Poorest Cluster dropped by an impressive half (50%). Oil consumption also fell dramatically from 2011 to 2012 for the Average and Poorest Clusters, again underscoring the effects of the deepening economic recession on lower-income population strata. As expected, the households of the Poorest Cluster spent less on electricity per month (in total and per m² of living space).

Finally, the FPR equalled 7.6% for the Richest Cluster, 8.6% for the Average Cluster and 11.6% for the Poorest Cluster, showing that the lowest income households were in more dire economic conditions than the rest of the low-income homes. This was despite the fact that the FPR was underestimated given that it did not include the cost of other heating means (which were used by more than 80% of households). These omissions may in part explain why the FPR values estimated in this research are somewhat lower than those found in a 2004 Athens survey (Santamouris et al., 2007).

So far, it has been established that the 50 households are grouped into three clusters: the richest, the average and the poorest households. Attention now turns to the analysis of the temperature measurements.

Analysis of temperature measurements

In this section, the entire sample period is considered, spanning indoor temperature measurements taken from 13 December 2012 to 15 April 2013. The sample is structured as an unbalanced panel data set (Frees, 2004) that includes 50 cross-sectional units (households), each of which contains a few thousand half-hourly indoor temperature time series observations that start at different points within this time period and all end on 15 April 2013. The house labelled as T3DEMER is the only household that was measured for the entire period (5913 observations), while house T28KAKAB had the fewest measurements (2016). According to Kennedy's (2008) characterization, the unbalanced panel data set at hand is long and wide.

To get an idea about the indoor temperature variation, the measurements of T3DEMER are shown in Figure 8, plotted with different symbols for each month. One can observe an overall nonlinear trend, with the lowest temperatures appearing in January or February 2013. Within each month, the indoor temperature varied in response to climatic conditions (e.g. ambient temperature), thermal conditions in each household and the heating patterns used by its occupants. This was more or less the case in most households.

A note on the use of ambient temperature data is due at this point. Various public organizations such as the Hellenic National Meteorological Service, the National Observatory of Athens, the National Agricultural Research Foundation and Harokopio University maintain a network of weather stations in and around Athens, Greece, and possess historical ambient temperature measurements (among other meteorological information). While it may seem useful to employ daily ambient temperature data as a predictor of indoor temperatures, such historical

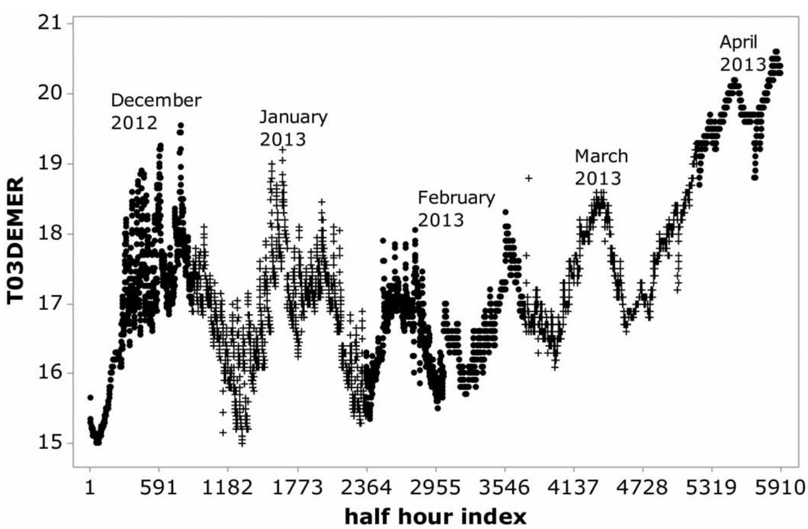

Figure 8. Time series plot of temperature measurements for T03DEMER household.

data are only available for a small number of fixed-location weather stations in the area of Athens, thus failing to take into account local and microclimatic conditions that are much more important in determining the indoor temperature. In addition, the typical hourly variation in ambient temperature is not correlated to indoor temperatures which, as will be seen later, in fact peak in the late evening hours as families reunite after work and attempt to heat their homes.

To account for seasonal change, month dummies were introduced (M12DUM, M01DUM, MO2DUM, MO3DUM and MO4DUM for December 2012, January 2013, February 2013, March 2013 and April 2013, respectively). These dummies equalled one for observations that were carried out in the respective month and zero for all other observations. Similarly, to consider variations from one day of the week to another (including weekends), day dummies were introduced (MONDAY to SUNDAY) that equalled one for observations that were carried out on the respective day of the week and zero for all others. Finally, the diurnal variation in temperature measurements was taken into account via the introduction of hour dummies, H00DUM to H23DUM for midnight (zero hours) to 11 pm (23 hours), respectively; these dummies were set equal to one when an observation was taken in the respective hour and zero for all other observations. With the aid of these three sets of dummies, an observation could be fully identified as having taken place at a particular time and date, for example, in January 2013 (M01DUM = 1, all four other monthly dummies being zero), on a Wednesday (WEDNESDAY = 1, all six other day of the week dummies being zero) at 8 am (H08DUM = 1, all 23 other hour dummies being zero). To avoid the trap of perfect multicollinearity (Gujarati, 2004), M12DUM, SUNDAY and H00DUM were omitted from the estimated regression models.

As noted previously in relevance to the temperature measurements of the T03DEMER house, all 50 indoor temperature measurements are time series that are stationary around a nonlinear (possibly quadratic) term. Theory dictates that indoor temperature measurements cannot be nonstationary because any weather shocks do not persist in the climatic system, and they certainly cannot be explosive since they are by their nature confined to a relatively narrow range around the seasonal temperature. As shown in Figure 8 for house T03DEMER, the observations testify to this, as they do not drift away from their average seasonal trend (not shown) but return to it and cross it often. Also, they are not mere white noise because there is a discernible structure in their variation through the year. As a result of this, it was preferred that the temperature measurement times series be analysed as stationary processes with appropriate corrections for serial correlation rather than carrying out unit root testing and transforming them as needed to achieve stationarity, that is, detrending them or taking their first differences before estimating any regression models (Brooks, 2014).

To understand and model the variation in temperature measurements (indicated by the variable TEMP) among houses and over time, two analytical approaches were adopted. First, 50 separate regressions were estimated, one for each house's temperature time series, as shown in Equation (3).

$$\begin{aligned}\mathrm{TEMP}_i = b_{i0} + b_{i1}\mathrm{M01DUM} + b_{i2}\mathrm{M02DUM} + \ldots + b_{i4}\mathrm{M04DUM} + \\ b_{i5}\mathrm{MONDAY} + b_{i6}\mathrm{TUESDAY} + \ldots + b_{i10}\mathrm{SATURDAY} + \\ b_{i11}\mathrm{H01DUM} + b_{i12}\mathrm{H02DUM} + \ldots + b_{i33}\mathrm{H23DUM} + u_i.\end{aligned} \tag{3}$$

The symbol b_{i0} is the constant; b_{i1} to b_{i33} are the slopes; and subscript i refers to household i, varies from 1 to 50, and is a reminder that there are 50 such regressions; an observation subscript has been omitted from the above equation for clarity. The significance (or lack thereof) of the constant is disregarded (and indeed not noted in any of the ensuing tables) as dictated by statistical theory (Studenmund, 2005). Since the temperature times series (dependent variable, also called response or regressand) displayed strong serial correlation (also termed autocorrelation; confirmed by autocorrelation function and partial autocorrelation function diagrams, not shown) that was not explained by any of the independent variables (also called predictors or regressors), the errors in Equation (3), symbolized by u_i, were also plagued by strong serial correlation. Therefore, ordinary least squares (OLS) was not the appropriate estimation procedure and it was decided that an AR(1) autoregression should be estimated with the Hildreth-Lu search procedure (Pindyck & Rubenfeld, 1991; Yaffee & McGee, 2000) that employs the Cochrane-Orcutt method for fine-tuning (Cottrell & Lucchetti, 2014), and heteroskedasticity and autocorrelation consistent (HAC) standard errors. The Hildreth-Lu search procedure, with results fine-tuned by the Cochrane-Orcutt method, was preferred to the Prais-Winsten algorithm because it tended to provide marginally better fits. Although, as Kamenta (1986) has reported, estimation algorithms that do not drop the first observation perform better, this was of no concern here due to the very large sample size. The AR(1) autoregression was identical to Equation (3) with the addition of the first lag of the response variable (temperature) among the predictors. The results of these 50 AR(1) models are shown in Table 4 (with the coefficient of the lagged temperature regressor not shown).

A word of caution on statistical significance is due at this point: although Tables 4 and 5 mark regression coefficients for statistical significance at the 90%, 95% and 99% confidence levels, high significance values should not be regarded as overly impressive because they are expected due to the very large size of the sample. On the contrary, one should interpret such results with caution for fear of committing Type II errors (Park, 2011).

To turn to model interpretation, judging by the satisfactory Durbin–Watson values, it is concluded that first-order autocorrelation is not a big issue thanks to the introduction of the lagged value of the dependent variable (temperature); what little autocorrelation remains is taken care of by the HAC standard errors. The models fit the data remarkably well, as evidenced by the adjusted R^2 values that are around 0.99 (although high values are to be expected with time series data) and confirmed by residual plots (not shown).

Comparing the 50 regression models, one observes that the most significant coefficients are those of the hour dummies, underscoring the importance of temperature variation throughout the day. Since the dummy H00DUM was omitted from Equation (3) to avoid perfect multicollinearity, it is understood that the coefficients of the other hour dummies (H01DUM to H23DUM) equal the difference in temperature from the hour of midnight to each of the other hours. The signs of these coefficients show that the warmest temperatures are encountered during the evening and late evening hours, as the families reunite at home after school and work. That the morning hours are in fact among the coldest shows that these economically impoverished households tended not to warm their houses at all in the period between waking up and getting ready for work.

Turning to the weekday dummies, one can observe no discernible pattern and only occasional statistical significance in some of the 50 regression models, showing that the day of the week is not much of a determinant of indoor temperature. Finally, although not all month dummies were available for all 50 households (since temperature measurements were not available for the entire period of December 2012 to April 2013 for all 50), the available coefficients (interpreted with their statistical significance) indicate a mild warming effect towards the spring, as expected.

An interesting conclusion may emerge from the results shown in Table 4; to appreciate the logic driving it, one has to consider an important fact first. If Equation (3) were estimated as an OLS regression with no lagged temperature regressor, the month and weekday dummies would be more statistically significant, falsely driving the conclusion that families managed to achieve warmer weekends (i.e. Saturdays and Sundays) and higher temperatures during the favourable spring months. In fact, the fit of such OLS regression models would suffer from extreme first-order autocorrelation (indicated by Durbin–Watson statistics close to zero) as well as heteroskedasticity (confirmed by residual plots), which tend to produce artificially small

Table 4. Separate temperature Hildreth-Lu AR(1) regressions with HAC standard errors.

	T01AMAL	T02GRIG	T03DEMER	T04DIAL	T05IOANK	T06IOANL	T07KARR	T08KONT	T09LAGOUT	T10LYBER
T (time periods)	5627	3168	5913	5568	5578	5867	5862	5866	3324	5541
R^2 adjusted	0.998	0.999	0.992	0.998	0.996	0.997	1.000	0.999	0.984	0.995
Durbin–Watson	1.461	2.357	1.512	2.070	1.543	1.272	1.816	1.860	1.762	1.368
Constant	18.761	30.519	17.412	18.509	17.525	17.703	25.134	30.180	17.274	17.125
M01DUM	0.064		−0.061	0.011	−0.111	−0.028	−0.088*	−0.072		−0.090
M02DUM	0.049		0.193	0.018	−0.096	0.002	−0.084	−0.002		−0.007
M03DUM	0.086	0.000	0.218	0.026	−0.176	0.035	−0.081	0.019	−0.053	0.032
M04DUM	0.120	−0.001	0.221	0.047	−0.149	0.077	−0.068	0.023	0.031	0.100
MONDAY	0.005	−0.003	0.006	0.000	−0.012	−0.019	−0.004	0.012	−0.018	−0.030
TUESDAY	0.027	−0.017	0.040	0.006	0.006	−0.024	−0.008	−0.001	−0.047	−0.013
WEDNESDAY	0.022	−0.020	0.100***	0.006	−0.011	−0.022	0.000	0.011	−0.018	0.026
THURSDAY	0.026	−0.012	0.093***	0.000	0.000	−0.023	0.005	0.003	0.010	−0.010
FRIDAY	0.028	−0.015	0.075**	0.012	−0.004	−0.034*	0.009	−0.002	0.030	−0.010
SATURDAY	0.005	−0.007	0.033	−0.004	0.019	−0.022	−0.002	−0.001	0.045	−0.009
H01DUM	−0.035***	0.002	−0.011	−0.007	−0.017**	−0.023***	−0.009**	−0.021***	−0.035	−0.010
H02DUM	−0.080***	0.002	0.007	−0.006	−0.023*	−0.048***	−0.017***	−0.042***	−0.091**	−0.022
H03DUM	−0.126***	−0.001	0.017	0.001	−0.025*	−0.072***	−0.024***	−0.063***	−0.154***	0.014
H04DUM	−0.168***	−0.009	0.019	0.005	−0.032**	−0.098***	−0.030***	−0.087***	−0.191***	0.013
H05DUM	−0.203***	−0.019	0.014	0.005	−0.032*	−0.110***	−0.039***	−0.111***	−0.189***	0.008
H06DUM	−0.253***	−0.033**	0.012	0.003	−0.038**	−0.127***	−0.050***	−0.137***	−0.217***	−0.009
H07DUM	−0.290***	−0.045***	0.006	−0.005	−0.036*	−0.150***	−0.057***	−0.164***	−0.217***	−0.028
H08DUM	−0.317***	−0.047***	−0.021	−0.018	−0.018	−0.171***	−0.040***	−0.165***	−0.241***	−0.043*
H09DUM	−0.314***	−0.048***	−0.072***	−0.019	0.034	−0.184***	−0.006	−0.199***	−0.230***	−0.034
H10DUM	−0.253***	−0.038**	−0.110***	−0.004	0.031	−0.173***	0.022**	−0.233***	−0.190***	−0.015
H11DUM	−0.217***	−0.014	−0.139***	0.003	0.021	−0.153***	0.017	−0.254***	−0.115	0.009
H12DUM	−0.166***	−0.002	−0.159***	0.052***	0.018	−0.125***	−0.005	−0.254***	−0.039	0.027
H13DUM	−0.092***	−0.001	−0.164***	0.059***	0.016	−0.083***	−0.010	−0.230***	0.016	0.043*
H14DUM	−0.008	−0.004	−0.145***	0.045***	0.021	−0.053***	−0.014	−0.189***	0.130*	0.063***
H15DUM	0.063***	−0.005	−0.145***	0.054***	0.018	−0.005	−0.014	−0.139***	0.244***	0.074***
H16DUM	0.116***	0.005	−0.136***	0.067***	0.006	0.039***	−0.009	−0.094***	0.621***	0.071***
H17DUM	0.142***	0.006	−0.135***	0.066***	−0.007	0.060***	−0.017*	−0.050***	0.536***	0.068***
H18DUM	0.166***	0.007	−0.155***	0.056***	−0.017	0.062***	−0.011	−0.024*	0.255***	0.056***
H19DUM	0.151***	−0.002	−0.185***	0.046***	−0.019	0.053***	−0.001	−0.026**	0.169***	0.047**
H20DUM	0.138***	−0.009	−0.152***	0.034***	−0.006	0.042***	0.002	−0.017	0.132**	0.038**
H21DUM	0.120***	−0.008	−0.107***	0.023**	0.009	0.032***	0.016**	0.000	0.081*	0.038**
H22DUM	0.083***	−0.005	−0.106***	0.022**	0.016	0.029***	0.014**	0.023***	0.079**	0.022*
H23DUM	0.037***	−0.002	−0.026***	0.017***	0.007	0.018***	0.009*	0.017***	0.035	0.026***

Table 4. Continued

	T11DESP	T12BREH	T13MOLG	T14STAVR	T15TOUR	T16KARA	T17SPAN	T18XEST	T19MOLV	T20RAPT
N	5808	5808	5616	5616	5568	5520	5472	5808	5616	3331
R^2 adjusted	0.997	0.975	0.966	0.994	0.991	0.990	0.986	0.993	0.993	0.993
Durbin–Watson	1.744	1.593	1.451	1.969	1.441	2.165	1.623	1.755	2.031	1.946
Constant	17.365	17.348	17.938	17.056	15.915	15.820	17.300	15.786	16.839	17.254
M01DUM	−0.110	−0.122	−0.482**	−0.040	−0.011	0.030	−0.105	−0.019	−0.050	0.015
M02DUM	−0.106	−0.318	−0.193	−0.018	−0.064	0.148	−0.035	0.098	−0.035	0.104
M03DUM	−0.099	−0.356	0.072	−0.093	−0.152	0.134	0.022	0.315	−0.105	−0.051
M04DUM	−0.074	−0.027	0.634**	−0.069	−0.063	0.108	0.093	0.317	−0.053	−0.046
MONDAY	−0.028	−0.032	0.037	−0.023	−0.108**	0.003	−0.033	−0.039	−0.012	−0.028
TUESDAY	−0.030	−0.008	0.001	0.008	−0.054	−0.002	0.053	−0.034	−0.050	−0.051
WEDNESDAY	0.010	−0.038	0.041	0.089**	−0.097	−0.021	0.030	−0.003	−0.048	−0.035
THURSDAY	0.002	0.009	0.037	0.076**	−0.114*	−0.005	0.004	0.011	−0.074*	−0.018
FRIDAY	−0.009	0.050	−0.014	0.058*	−0.026	−0.005	−0.017	−0.028	−0.062	−0.018
SATURDAY	−0.001	−0.010	−0.035	0.024	0.062	0.004	0.020	0.004	−0.003	−0.031
H01DUM	−0.001	−0.050**	−0.083***	−0.027***	−0.057***	−0.027*	0.038***	0.015	−0.034***	−0.066
H02DUM	−0.022*	−0.090**	−0.153***	−0.050***	−0.150***	−0.054**	0.039**	−0.021	−0.067***	−0.094*
H03DUM	−0.050***	−0.120***	−0.203***	−0.082***	−0.231***	−0.083***	0.004	−0.046	−0.113***	−0.120***
H04DUM	−0.087***	−0.152***	−0.256***	−0.102***	−0.291***	−0.109***	−0.030	−0.071**	−0.151***	−0.153***
H05DUM	−0.120***	−0.165***	−0.302***	−0.123***	−0.345***	−0.136***	−0.050*	−0.094**	−0.195***	−0.135***
H06DUM	−0.153***	−0.196***	−0.351***	−0.135***	−0.388***	−0.160***	−0.083***	−0.117***	−0.238***	−0.109***
H07DUM	−0.175***	−0.194***	−0.421***	−0.151***	−0.376***	−0.184***	−0.114***	−0.109**	−0.268***	−0.065***
H08DUM	−0.199***	0.067	−0.453***	−0.169***	−0.247***	−0.177***	−0.135***	−0.116***	−0.279***	−0.047***
H09DUM	−0.206***	0.195***	−0.507***	−0.178***	−0.083*	0.046	−0.164***	−0.100**	−0.274***	−0.045**
H10DUM	−0.181***	0.089	−0.491***	−0.150***	0.110**	−0.054	−0.151***	−0.082*	−0.256***	0.014
H11DUM	−0.144***	0.126**	−0.509***	−0.131***	0.254***	−0.054	−0.134***	−0.050	−0.221***	0.034
H12DUM	−0.129***	0.174***	−0.501***	−0.113***	0.402***	−0.015	−0.131***	−0.032	−0.193***	0.072
H13DUM	−0.082***	0.247***	−0.491***	−0.094***	0.533***	0.012	−0.111***	−0.009	−0.154***	0.082
H14DUM	−0.056**	0.271***	−0.482***	−0.081***	0.620***	0.045	−0.088***	0.005	−0.106***	0.080**
H15DUM	−0.049**	0.277***	−0.440***	−0.071***	0.640***	0.072*	−0.079**	0.034	−0.028	0.094***
H16DUM	−0.040*	0.259***	−0.410***	−0.070***	0.611***	0.083**	−0.068**	0.061	0.005	0.053***
H17DUM	−0.032	0.176***	−0.390***	−0.069***	0.478***	0.079**	−0.073**	0.052	0.033	0.032***
H18DUM	−0.041**	0.101*	−0.318***	−0.043*	0.275***	0.068**	−0.066**	0.010	0.041	0.029*
H19DUM	−0.019	0.076	−0.171***	−0.040*	0.164***	0.052*	−0.042	0.023	0.009	0.052
H20DUM	−0.011	0.072	−0.009	−0.030	0.098***	0.046	−0.030	0.042	−0.008	0.035
H21DUM	−0.022	0.049	0.108***	−0.039**	0.069**	0.036	−0.036	0.039	−0.021	0.020**
H22DUM	−0.015	0.046	0.158***	−0.016	0.041	0.033	−0.036*	0.029	−0.003	17.254*
H23DUM	−0.009	0.040	0.088***	−0.016	0.021	0.016	−0.027**	0.026	0.006	0.015

(*Continued*)

Table 4. Continued

	T21MAZA	T22ZEK	T23LAFAZ	T24MAZH	T25KAPS	T26TZOG	T27MAVR	T28KAKAB	T29TASS	T30SABIOL
N	5616	5424	5424	5616	2160	2160	2112	2016	2160	2160
R^2 adjusted	0.978	0.951	0.974	0.981	0.994	0.991	0.974	0.999	0.893	0.999
Durbin–Watson	1.184	1.566	1.342	1.319	1.212	1.723	1.824	1.904	1.916	2.162
Constant	19.171	17.070	18.693	19.658	18.441	18.193	20.058	20.402	19.064	17.951
M01DUM	0.489*	−0.240	0.001	0.013						
M02DUM	0.835**	0.203	0.075	0.112						
M03DUM	1.038**	1.316**	0.075	0.417						
M04DUM	1.691***	2.373***	0.211	0.872*	0.006	0.006	0.178	−0.056	0.888***	−0.049
MONDAY	−0.054	−0.080	0.003	−0.024	−0.026	0.069	0.108	−0.002	0.028	−0.016
TUESDAY	−0.019	−0.028	0.014	−0.028	−0.031	0.108	0.071	−0.024	−0.314	0.002
WEDNESDAY	0.115	−0.026	0.005	−0.014	−0.036	0.131	0.119	−0.020	−0.054	0.004
THURSDAY	0.132	0.117	0.011	−0.006	−0.007	0.188**	0.135	−0.015	0.062	0.005
FRIDAY	0.040	−0.016	0.008	−0.023	0.056	0.128*	0.086	0.007	−0.001	−0.010
SATURDAY	0.017	0.025	0.017	0.020	0.068	0.102*	0.053	−0.005	0.147	0.008
H01DUM	−0.262***	−0.114**	−0.065***	−0.309***	−0.165***	−0.079***	−0.110***	−0.060***	−0.097	−0.049***
H02DUM	−0.455***	−0.180***	−0.142***	−0.543***	−0.308***	−0.178***	−0.174***	−0.125***	−0.056	−0.086***
H03DUM	−0.598***	−0.226***	−0.209***	−0.734***	−0.450***	−0.285***	−0.241***	−0.201***	−0.229**	−0.137***
H04DUM	−0.722***	−0.365***	−0.271***	−0.894***	−0.575***	−0.384***	−0.312***	−0.278***	−0.143	−0.196***
H05DUM	−0.824***	−0.537***	−0.326***	−1.038***	−0.693***	−0.470***	−0.362***	−0.347***	−0.251*	−0.254***
H06DUM	−0.916***	−0.728***	−0.377***	−1.166***	−0.805***	−0.486***	−0.421***	−0.416***	−0.317**	−0.307***
H07DUM	−1.003***	−0.830***	−0.426***	−1.290***	−0.823***	−0.605***	−0.461***	−0.490***	−0.482***	−0.342***
H08DUM	−1.098***	−0.897***	−0.489***	−1.404***	−0.548***	−0.664***	−0.463***	−0.550***	−0.379**	−0.379***
H09DUM	−1.177***	−0.915***	−0.418***	−1.498***	−0.048	−0.687***	−0.285***	−0.589***	−0.462***	−0.356***
H10DUM	−1.241***	−0.929***	−0.269***	−1.545***	0.378***	−0.670***	−0.131	−0.570***	−0.446***	−0.298***
H11DUM	−1.266***	−0.860***	−0.186***	−1.473***	0.689***	−0.580***	0.086	−0.499***	−0.501***	−0.242***
H12DUM	−1.226***	−0.711***	−0.124***	−1.405***	0.905***	−0.450***	0.519***	−0.394***	−0.407***	−0.202***
H13DUM	−1.177***	−0.461***	−0.049	−1.255***	1.027***	−0.386***	0.838***	−0.290***	−0.363**	−0.141***
H14DUM	−0.957***	−0.199*	0.025	−0.955***	1.104***	−0.353***	0.830***	−0.197***	−0.313**	−0.079***
H15DUM	−0.715***	0.047	0.053	−0.600***	1.128***	−0.281***	0.464***	−0.112***	−0.244	0.006
H16DUM	−0.632***	0.241**	0.106**	−0.477***	1.075***	−0.111**	0.355***	−0.034	−0.215	0.087***
H17DUM	−0.673***	0.348***	0.167***	−0.479***	1.001***	−0.129**	0.287***	0.028	−0.180	0.125***
H18DUM	−0.736***	0.237**	0.280***	−0.509***	0.910***	−0.143***	0.196**	0.085***	−0.107	0.132***
H19DUM	−0.778***	0.232**	0.266***	−0.511***	0.781***	−0.155***	0.159*	0.104***	−0.048	0.132***
H20DUM	−0.744***	0.171*	0.251***	−0.470***	0.654***	−0.061	0.121	0.127***	−0.019	0.117***
H21DUM	−0.398***	0.212***	0.215***	−0.226***	0.522***	0.068*	0.123*	0.113***	−0.016	0.091***
H22DUM	0.094***	0.300***	0.139***	0.162***	0.342***	0.125***	0.097*	0.079***	0.024	0.056***
H23DUM	0.242***	0.140***	0.069***	0.268***	0.164***	0.057**	0.084*	0.043***	0.010	0.036***

Table 4. Continued

	T31GERON	T32KAIM	T33DIAM	T34BALAT	T35SFYR	T36PAPA	T37DRET	T38STERG	T39KOUV	T40PSIS
N	5862	5858	5860	5862	5860	5862	5862	5862	5862	3035
R^2 adjusted	0.987	0.996	0.993	0.997	0.999	0.998	0.991	0.994	0.997	0.998
Durbin–Watson	2.105	1.722	1.628	2.265	2.128	2.387	2.485	1.587	1.693	1.743
Constant	17.129	17.195	17.139	14.530	19.330	17.981	17.077	17.538	18.487	18.655
M01DUM	−0.051	−0.105	0.166	0.028	−0.074	0.154	0.151	−0.535***	0.090	
M02DUM	−0.217	−0.211	−0.031	−0.084	−0.116	0.143	0.109	−0.799***	0.005	
M03DUM	−0.064	−0.213	−0.067	−0.142	−0.207*	0.233*	0.149	−0.655**	0.023	−0.038
M04DUM	−0.025	−0.216	−0.046	0.068	−0.290**	0.227**	0.184	−0.713**	0.055	−0.011
MONDAY	0.003	0.013	0.016	−0.055	−0.004	0.000	0.009	−0.008	−0.016	0.029
TUESDAY	0.005	0.017	0.017	−0.037	−0.018	−0.012	0.003	−0.012	0.005	0.049
WEDNESDAY	−0.034	0.015	0.008	−0.015	−0.024	−0.024	0.009	−0.057	−0.005	0.047
THURSDAY	−0.053	−0.007	−0.031	0.005	−0.007	−0.015	−0.012	−0.048	−0.020	0.045
FRIDAY	0.092*	0.003	−0.062**	0.019	−0.003	−0.010	−0.003	−0.053	−0.022	0.037
SATURDAY	0.008	0.024	−0.070***	0.010	−0.006	−0.019	−0.003	−0.083**	−0.022	0.002
H01DUM	−0.052***	−0.023***	−0.038***	−0.069***	−0.020***	0.006***	−0.004	−0.052***	−0.015**	−0.059***
H02DUM	−0.083***	−0.071***	−0.059***	−0.120***	−0.046***	0.005***	−0.012	−0.164***	−0.039***	−0.117***
H03DUM	−0.098***	−0.116***	−0.069***	−0.160***	−0.068***	0.000***	−0.023	−0.266***	−0.070***	−0.169***
H04DUM	−0.117***	−0.168***	−0.089***	−0.210***	−0.095***	−0.009***	−0.029	−0.338***	−0.110***	−0.219***
H05DUM	−0.134***	−0.203***	−0.104***	−0.251***	−0.119***	−0.020***	−0.032	−0.401***	−0.134***	−0.265***
H06DUM	−0.146***	−0.241***	−0.117***	−0.298***	−0.145***	−0.026***	−0.041	−0.461***	−0.153***	−0.312***
H07DUM	−0.154***	−0.257***	−0.128***	−0.282***	−0.144***	−0.034***	−0.041	−0.512***	−0.162***	−0.330***
H08DUM	−0.194***	−0.272***	−0.154***	−0.357***	−0.201***	−0.043***	−0.039	−0.558***	−0.156***	−0.306***
H09DUM	−0.192***	−0.281***	−0.142***	−0.400***	−0.220***	−0.046***	−0.027	−0.589***	−0.165***	−0.218***
H10DUM	−0.213***	−0.286***	−0.155***	−0.392***	−0.222***	−0.047***	−0.011	−0.552***	−0.166***	−0.078***
H11DUM	−0.238***	−0.276***	−0.145***	−0.357***	−0.202***	−0.042***	0.008	−0.463***	−0.179***	0.091***
H12DUM	−0.250***	−0.259***	−0.144***	−0.297***	−0.174***	−0.041***	0.023	−0.340***	−0.170***	0.268***
H13DUM	−0.223***	−0.248***	−0.151***	−0.230***	−0.130***	−0.063***	0.045	−0.213***	−0.146***	0.373***
H14DUM	−0.241***	−0.233***	−0.154***	−0.153***	−0.090***	−0.072***	0.064**	−0.135***	−0.101***	0.458***
H15DUM	−0.231***	−0.223***	−0.149***	−0.073**	−0.048***	−0.084***	0.097***	−0.062*	−0.102***	0.510***
H16DUM	−0.216***	−0.204***	−0.137***	−0.021	−0.019	−0.085	0.137***	−0.017	−0.086***	0.518***
H17DUM	−0.238***	−0.177***	−0.141***	0.016	0.011	−0.081	0.116***	−0.058*	−0.087***	0.473***
H18DUM	−0.242***	−0.175***	−0.144***	0.058*	0.012	−0.073	−0.020	−0.098***	−0.072***	0.412***
H19DUM	−0.221***	−0.151***	−0.125***	0.090***	0.031**	−0.059**	−0.025	−0.081***	−0.041***	0.328***
H20DUM	−0.184***	−0.118***	−0.089***	0.111***	0.034***	−0.051***	−0.026	−0.047*	−0.013	0.255***
H21DUM	−0.143***	−0.072***	−0.044***	0.120***	0.036***	−0.040***	−0.024	−0.043*	0.008	0.186***
H22DUM	−0.091***	−0.028**	−0.006	0.122***	0.026***	−0.024***	−0.009	0.032	0.013	0.120***
H23DUM	−0.048***	0.000	0.017*	0.047***	0.014**	**	−0.001	0.005	0.011	0.054***

(*Continued*)

Table 4. Continued

	T41VOITS	T42ALEV	T43MANOU	T44TSIT	T45MOURT	T46SOTIR	T47ARVAN	T48TSIG	T49SVOUR	T50HARIT
N	5472	5472	5616	5616	5472	5616	5520	2640	2640	2640
R^2 adjusted	0.988	0.995	0.994	0.977	0.996	0.984	0.995	0.986	0.992	0.986
Durbin–Watson	1.254	2.221	1.113	1.569	1.911	1.767	1.736	2.098	1.920	1.921
Constant	16.966	17.628	17.752	17.346	18.069	17.594	16.947	17.580	18.122	18.135
M01DUM	0.158	0.041	0.010	0.047	0.088	0.224	0.030			
M02DUM	0.347	0.051	0.164	0.088	0.001	−0.107	0.398			
M03DUM	1.007***	0.260	0.226	1.110***	−0.085	0.260	0.424	−0.053	0.090	0.091
M04DUM	1.132***	0.230	0.328	1.660***	−0.048	0.570	0.401	−0.101	0.196	0.206
MONDAY	0.081*	−0.048	0.034	−0.021	−0.007	−0.009	0.032	−0.040	−0.071	−0.054
TUESDAY	0.009	−0.078	0.041	0.001	−0.069***	−0.017	−0.057	−0.099	−0.124*	−0.142*
WEDNESDAY	0.134**	−0.141***	0.068	0.050	−0.032	−0.058	−0.011	0.371***	0.009	−0.016
THURSDAY	0.017	−0.053	0.054	0.078	−0.019	−0.011	−0.001	0.210**	−0.001	0.081
FRIDAY	−0.021	−0.035	0.031	0.073	−0.003	−0.125	−0.011	0.118	0.016	−0.008
SATURDAY	−0.011	−0.057	−0.029	0.077	0.000	−0.042	0.035	0.096	0.020	0.027
H01DUM	−0.042**	−0.031**	−0.099***	−0.060***	−0.017**	−0.083***	−0.027*	−0.056**	0.009	−0.036
H02DUM	−0.089***	−0.058***	−0.176***	−0.120***	−0.039***	−0.173***	−0.028	−0.087**	−0.007	−0.075**
H03DUM	−0.129***	−0.091***	−0.240***	−0.192***	−0.058***	−0.232***	−0.036	−0.099**	−0.032	−0.087**
H04DUM	−0.174***	−0.121***	−0.298***	−0.236***	−0.069***	−0.301***	−0.027	−0.119**	−0.037	−0.107**
H05DUM	−0.192***	−0.161***	−0.357***	−0.276***	−0.086***	−0.364***	−0.047	−0.135**	−0.051	−0.144***
H06DUM	−0.178***	−0.177***	−0.404***	−0.301***	−0.095***	−0.425***	−0.082**	−0.147**	−0.061	−0.158***
H07DUM	−0.136***	−0.109***	−0.453***	−0.191***	−0.111***	−0.483***	−0.098***	−0.091	−0.081	−0.125**
H08DUM	−0.047	−0.143***	−0.502***	−0.203***	−0.120***	−0.531***	−0.125***	−0.177***	−0.121**	−0.088
H09DUM	−0.113**	−0.192***	−0.562***	−0.278***	−0.125***	−0.602***	−0.152***	−0.215***	−0.144***	−0.165 ***
H10DUM	−0.175***	−0.240***	−0.626***	−0.335***	−0.117***	−0.660***	−0.161***	−0.244***	−0.192***	−0.257***
H11DUM	−0.207***	−0.270***	−0.648***	−0.356***	−0.106***	−0.662***	−0.172***	−0.254***	−0.214***	−0.285***
H12DUM	−0.225***	−0.228***	−0.639***	−0.353***	−0.098***	−0.680***	−0.157***	−0.223***	−0.202***	−0.263***
H13DUM	−0.257***	−0.206***	−0.595***	−0.345***	−0.078***	−0.638***	−0.130***	−0.239***	−0.214***	−0.240***
H14DUM	−0.265***	−0.169***	−0.501***	−0.280***	−0.069***	−0.608***	−0.096**	−0.225***	−0.210***	−0.157***
H15DUM	−0.251***	−0.146***	−0.381***	−0.189***	−0.060***	−0.533***	−0.064	−0.188***	−0.189***	−0.042
H16DUM	−0.235***	−0.098***	−0.265***	−0.146***	−0.057***	−0.438***	−0.072*	−0.124*	−0.205***	0.036
H17DUM	−0.228***	−0.049	−0.202***	−0.185***	−0.038**	−0.299***	−0.062*	−0.027	−0.174***	0.042
H18DU	−0.171***	−0.044	−0.161***	−0.230***	−0.039***	−0.220***	−0.023	−0.102*	−0.208***	−0.055
H19DUM	−0.097**	−0.061**	−0.119***	−0.195***	−0.032**	−0.112**	−0.041	−0.127**	−0.192***	−0.078*
H20DUM	−0.037	−0.057**	−0.038	−0.152***	−0.012	0.047	−0.023	−0.143***	−0.137***	−0.095**
H21DUM	0.027	−0.052**	0.056***	−0.093**	0.004	0.106***	−0.013	−0.087*	−0.096***	−0.074*
H22DUM	0.029	−0.028	0.194***	−0.040	0.019**	0.135***	−0.012	−0.076*	−0.005	−0.039
H23DUM	0.048**	0.001	0.105***	−0.009	0.026***	0.085***	−0.015	−0.071**	0.003	−0.012

*.05 < p < .1; **.01 < p < .05; ***p < .01.

Table 5. Pooled OLS regressions with Arellano robust standard errors.

	TEMP	TEMP
N	209,368	209,368
households	44	44
R^2 adjusted	0.992	0.992
Durbin–Watson	1.490	1.490
Constant	0.070	0.074
TEMP_1	0.992***	0.992***
M01DUM	−0.001	−0.001
M02DUM	0.003	0.002
M03DUM	0.012***	0.012***
M04DUM	0.029***	0.029***
MONDAY	−0.004**	−0.004**
TUESDAY	−0.001	−0.001
WEDNESDAY	−0.001	−0.001
THURSDAY	−0.001	−0.001
FRIDAY	−0.003	−0.003
SATURDAY	0.001	0.001
H01DUM	−0.007**	−0.007**
H02DUM	−0.002	−0.002
H03DUM	0.000	0.000
H04DUM	0.002	0.002
H05DUM	0.001	0.001
H06DUM	0.004	0.004
H07DUM	0.018**	0.018**
H08DUM	0.024**	0.024**
H09DUM	0.043***	0.043***
H10DUM	0.036***	0.036***
H11DUM	0.055***	0.055***
H12DUM	0.066***	0.066***
H13DUM	0.075***	0.075***
H14DUM	0.084***	0.084***
H15DUM	0.081***	0.081***
H16DUM	0.072***	0.072***
H17DUM	0.042***	0.042***
H18DUM	0.035***	0.035***
H19DUM	0.048***	0.048***
H20DUM	0.059***	0.059***
H21DUM	0.076***	0.076***
H22DUM	0.066***	0.066***
H23DUM	0.030***	0.030***
M2		0.000
ROOMS		0.002
MEMBERS		−0.001
BUILDAGE		0.000
INCOME3		0.001*
RICHEST	0.015**	
AVERAGE	0.012*	
UNEMPLOYED	0.000	−0.001
PENSIONER	0.003	0.005*
APARTMENT	−0.011***	−0.012***
INSULATION	0.000	0.002
AC	0.002	0.002
OILITER2012	0.000	0.000
FUELPOV2012	0.001*	0.001

*.05 < p < .1; **.01 < p < .05; ***p < .01.

standard errors and, thus, misleadingly high statistical significance (Gujarati, 2004; Studenmund, 2005). Instead, Equation (3) was estimated correctly as an AR(1) with robust standard errors, improving the model fit dramatically and raising the value of the Durbin–Watson statistic to the vicinity of two, showing much less (if any) remaining serial correlation with no heteroskedasticity; at the same time, the statistical significance of the month and weekday dummies was reduced, leaving only the hour of the day as an important determinant of indoor temperature. So, one may ask, what is the significance of this? The most plausible explanation could only be that, although the arrival of spring may give the impression that families have control over the indoor temperatures of their houses, in fact they only have some control over the diurnal temperature variation, that is, creating some relative warmth late in the evening and at night, by heating their homes. Other than that, the models estimated correctly show that they are, unfortunately, clearly constrained by the conditions of their household and its environment, such as the building envelope or the microclimatic conditions around their home. Although such influences constitute omitted variables and likely introduce some bias into Equation (3) (Gujarati, 2004; Studenmund, 2005), the superior estimation afforded by the AR(1) regression models highlights the limited control that a low- or very-low-income family has at its disposal as it battles the near-freezing temperature lows measured in these deprived households.

Attention now shifts to a second approach to the analysis of the temperature measurements. Analysing the temperature measurements as separate time series, one for each household, allowed the development of 50 regression models that could be compared with one another, thus shedding light on temperature variations in specific households. Yet, such an approach did not allow, by design, the incorporation of regressor variables that remain constant for each household, such as building characteristics and family income. The effect of variables that vary from one household to another can only be assessed by an analysis that pools all individual household measurements into one long data set with the unbalanced panel data structure mentioned earlier. In such an analysis, each month, weekday and hourly dummy will have a single coefficient for all 50 households, prohibiting any such comparisons among households. These two analytical approaches are thus complementary and together afford a comprehensive look into the way indoor temperature fluctuates in low- and very-low-income households.

The single model estimated in this approach is shown below:

$$\begin{aligned} \mathrm{TEMP} = b_0 + b_1\mathrm{M01DUM} + b_2\mathrm{M02DUM} + \ldots + b_4\mathrm{M04DUM} + \\ b_5\mathrm{MONDAY} + b_6\mathrm{TUESDAY} + \ldots + b_{10}\mathrm{SATURDAY} + \\ b_{11}\mathrm{H01DUM} + b_{12}\mathrm{H02DUM} + \ldots + b_{33}\mathrm{H23DUM} + \\ b_{34}\mathrm{RICHEST} + b_{35}\mathrm{AVERAGE} + b_{36}\mathrm{UNEMPLOYED} + b_{37}\mathrm{PENSIONER} + \\ b_{38}\mathrm{APARTMENT} + b_{39}\mathrm{INSULATION} + b_{40}\mathrm{AC} + \\ b_{41}\mathrm{OILITER2012} + b_{42}\mathrm{FUELPOV2012} + u, \end{aligned} \tag{4}$$

where the i subscript has now been omitted to denote the fact that this is a single regression model that will be estimated for the pooled data of all households. It may be noted that participation in the Richest and Average Clusters, determined in the previous section, has been accounted for with the inclusion of corresponding dummies; membership of the Poorest Cluster will be signified by both of these dummies being equal to zero. The rest of the exogenous variables are labelled in a self-explanatory fashion and were chosen both for theoretical reasons (eminence in the research literature) and practical ones (few missing data points, so that few of the 50 households would be omitted by the listwise deletion of observations with missing data, carried out before the estimation of the regression of the above equation).

For reasons stemming from the serial correlation of the temperature measurement time series, and arguments similar to the ones made about the previous analytical approach, it was decided that a pooled OLS panel data autoregression should be estimated with HAC standard errors as suggested by Arellano (1987) for within-group analyses, which essentially assumes that regression errors are uncorrelated across the different cross-sectional units (Stock & Watson, 2011). The estimation results for Equation (4) are shown in the left-hand TEMP column of Table 5, with TEMP_1 signifying the temperature lag added to Equation (4).

The overall model fit is impressively good, with an adjusted R^2 of 99.2%. The Durbin–Watson statistic of 1.490 shows that some serial correlation (most likely caused by randomness impossible to account for) may remain, thus providing justification for the use of Arellano robust standard errors. While the coefficients of January (M01DUM) and February (M02DUM) of 2013 are insignificant, those of March (M02DUM) and April (M04DUM) of 2013 have a positive sign and are highly significant, showing the effect of warming weather conditions with the advent of spring. Hour dummies now draw a slightly different picture from the previous models, showing a significant increase in indoor temperature especially in the afternoon and late evening hours, holding everything else, including the exogenous household and socioeconomic regressors included in Equation (4), constant. Of these peaks, the afternoon one may be attributed to the peak in ambient temperature and the late evening one to the family heating the house. Again, these are overall trends, describing the average conditions in a typical home, while the separate time series models of Table 4 are more accurate in describing the conditions in each household individually.

Of great interest are the positive coefficients that show membership of the Richest and Average Clusters. These exert an effect on temperature weaker than the hourly and comparable to the monthly dummy variables but significant (to a confidence level of 95% or higher) nonetheless. Clearly the Poorest Cluster contains the most deprived homes and this is reflected in the indoor temperatures.

The coefficients of the rest of the exogenous variables are not statistically significant, except for the apartment dummy (APARTMENT, indicating an apartment rather than a detached home) and the FPR for 2012 (FUELPOV2012). The coefficient of the apartment dummy shows that the apartments were colder than the detached houses. The FPR was positively correlated with the indoor temperature; this was unexpected but it may be explained by considering that more fuel-poor households may in fact manage to do a little better thermally by resorting to heating sources other than oil or electricity (the only ones taken into account in the computation of the FPR in this research).

Since the data set was very large and degrees of freedom were not a constraint, a second regression was estimated, this time incorporating the five individual variables that were used in the cluster analysis (rather than cluster membership): M2, ROOMS, MEMBERS, BUILDAGE and income expressed in 1000 euros (INCOME3, which represents the income expressed in 1000 euros). The results of this second estimation are shown in the right-hand TEMP column of Table 5 and are almost identical to those of the previous estimation. This time, the coefficient of INCOME3 is significant and has a positive sign, showing (as expected) that richer families had higher indoor temperatures (keeping everything else constant). Finally, the pensioner dummy was significant, showing that pensioners tended to maintain warmer homes (with all other effects kept constant).

This concludes the analysis of the temperature measurements as well as the results section of this paper.

Conclusions

The fuel poverty and indoor temperature research presented here found that low- and very-low-income households in Athens, Greece, are clustered in three groups; the poorest ones include very-low-income families, with few members, living in older and smaller households, and using less heating; the richest ones are larger families with higher incomes, living in newer buildings, occupying a larger surface area with more rooms and using more heating autonomy. Indoor temperatures were found to be below accepted standards, reaching as low as 5°C. The analyses showed that these families were able to exercise limited control as they tried to heat their homes, which they mostly did during the late evening when the working family members returned from work. One can only wonder how older and younger household members who stayed at home during the day managed to get by in such dismal thermal conditions. Interestingly, it can be concluded that fuel poverty likely motivates people to use, with some success, heating sources other than the oil, natural gas and electricity that were recorded in this study.

These low- and very-low-income households that are trapped by dire socioeconomic conditions and constrained by their building infrastructure need help to achieve adequate warmth in their severely deprived homes. Santamouris et al. (2014) mention that low-income households in Greece live in inadequately protected houses that require a high energy load to heat and cool. Although beyond the scope of this work, the research of Sakka, Santamouris, Livada, Nicol, and Wilson (2012), who found indoor temperatures to be as high as 40°C in 50 low-income non-air-conditioned houses in Athens, Greece, during three extended heat waves during the summer of 2007, shows another aspect of fuel poverty that is particularly eminent in countries with bioclimatic conditions similar to Greece. All in all, there remains little doubt that such households constitute a large part of the aforementioned 15–25% of the low-income population in Southern Europe that has been hit hard by the deepening economic recession and will continue to struggle in both winter and summertime. This group should be targeted by specific measures and programmes so that they are able to achieve thermal conditions compatible with the good health and prosperity expected of a European citizen in the twenty-first century. This research agrees with the previously mentioned authors that measures aiming to supply sufficient heating energy at low prices, together with programmes to improve the thermal performance of low- and very-low-income houses, have to be defined and undertaken as a national and regional priority.

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