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A panel model for predicting the diversity of internal temperatures from English dwellings[1]

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Abstract

Using panel methods, a model for predicting daily mean internal temperature demand across a heterogeneous domestic building stock is developed. The model offers an important link that connects building stock models to human behaviour. It represents the first time a panel model has been used to estimate the dynamics of internal temperature demand from the natural daily fluctuations of external temperature combined with important behavioural, socio-demographic and building efficiency variables. The model is able to predict internal temperatures across a heterogeneous building stock to within ~0.71°C at 95% confidence and explain 45% of the variance of internal temperature between dwellings. The model confirms hypothesis from sociology and psychology that habitual behaviours are important drivers of home energy consumption. In addition, the model offers the possibility to quantify take-back (direct rebound effect) owing to increased internal temperatures from the installation of energy efficiency measures. The presence of thermostats or thermostatic radiator valves (TRV) are shown to reduce average internal temperatures, however, the use of an automatic timer is statistically insignificant. The number of occupants, household income and occupant age are all important factors that explain a proportion of internal temperature demand. Households with children or retired occupants are shown to have higher average internal temperatures than households who do not. As expected, building typology, building age, roof insulation thickness, wall U-value and the proportion of double glazing all have positive and statistically significant effects on daily mean internal temperature. In summary, the model can be used as a tool to predict internal temperatures or for making statistical inferences. However, its primary contribution offers the ability to calibrate existing building stock models to account for behaviour and socio-demographic effects making it possible to back-out more accurate predictions of domestic energy demand.

Keywords: temperature, rebound effect, buildings, domestic, energy, demand, behaviour, panel

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1 Introduction

1.1 Background

In the UK, the built environment accounts for approximately 40% of primary energy demand of which 60% is used for home heating, 20% for hot water and the remaining 20% for lighting and appliances [1]. In 2011 almost 90% of all UK dwellings used central heating systems as a primary heat source. Thus a transition from individual room fires and heaters to more modern, controllable central heating systems has dramatically changed the way in which people use energy in their homes. Although modern gas central heating systems are arguably much more energy efficient, they also provide users with instantaneous heating[1] and thus create opportunities for increased energy consumption. This is for several reasons. First, they benefit from advanced controls and automation giving functionality and flexibility that are simply not available with more traditional heating methods. Secondly, little effort is required to increase consumption unlike traditional wood and coal fired heating systems. Finally, central heating has introduced the capability to heat every room in the house through dedicated radiators. As will be discussed, the repercussions of modern heating systems and controls on internal temperature profiles are still widely disputed. For example, Shipworth [2] shows there is no evidence that thermostat settings have changed between 1984 and 2007. Shipworth suggests that despite overall efficiency gains, the absence of a reduction in energy consumption may be explained by an increase in the total area of the dwelling now being heated, an increase in heating duration and an increase in the frequency of window openings to control temperature.

Because home heating contributes towards a significant component of total residential energy consumption, it is worthwhile scrutinizing the driving forces behind demand for home heating. A growing body of literature suggests that home heating is just as much due to the behavioural and social characteristics of people and how they interact with energy technology as it is to do with the physical properties and efficiency of the building [3–6]. The idea that people matter as much as buildings was pioneered by Lutzenhiser [7] where he argued that psychological, social, economic and behavioural aspects must be considered alongside the physical properties of the building. In his seminal paper Lutzenhiser coined this as the 'cultural model' of energy use. Following Lutzenhiser, Hitchcock [8] argued the need for a systems based framework, able to integrate the social and technical aspects of energy demand into a single model. In his analysis Hitchcock asserts that "energy consumption patterns are a complex technical and social phenomenon" and thus to be fully understood must be "viewed from both engineering and social science perspectives concurrently". Although both authors made the intellectual leap to bring two very distinct

[1] "Instantaneous heating" refers to the activation of the system, central heating systems still typically take approximately 30-90 mins for a dwelling to reach set-point temperatures.

research approaches together, many of the building stock models developed over the following several decades have never managed to fully incorporate these early ideas [9,10].

Since these early pioneers, most research has attempted to model and understand home energy demand through a deeper understanding of society (sociology) and human behaviour (psychology) [4,11–13]. Alternatively engineering models have attempted to build more accurate instrumentation and calculation algorithms to improve the accuracy of modelling heating systems and heat loss through building envelopes [14,15]. Investigations in each research discipline have therefore grown in both scope and scale for the type of problems that can be considered, but neither has fully incorporated the beneficial advances made by the other discipline. Some authors, however, have started to develop bottom-up engineering models that utilise proxy variables to represent human behaviour. For example, Brown et al [16] has developed a model utilising water consumption as a proxy for occupancy. Inroads have also been laid by Richardson et al. [17] where time of use surveys have been used to estimate occupancy patterns and domestic energy demand profiles of dwelling inhabitants. Although such studies provide a glimpse of what energy profiles might look like at the individual building level, such information has never been combined and integrated within a national building stock model requiring much larger samples from a heterogeneous building stock. Even today there is still not a well defined path for how human behaviour may be accurately incorporated in bottom-up engineering building stock models. This assertion is supported by Audenaert [18] who claims there is a clear gap in understanding the different behavioural factors that lead to an occupant's demand for heating, and calls for more research that identifies these driving factors.

The importance of behavioural and social factors is highlighted in a study by Gill and Tierney [19] where it is found that behaviour accounts for 51%, 37% and 11% of the variance in heat, electricity and water consumption respectively across different dwellings. Implicitly this suggests that models neglecting human behaviour in the estimation of home energy consumption can be out by as much as ±50%. However, the majority of residential stock models do not take social and behavioural factors into consideration. Top down models neglect behavioural factors, simply because it is not possible to aggregate dwelling level behaviour into any meaningful aggregate statistic of the entire building stock. On the other hand, bottom-up models are dominated by engineering building physics models that only consider the physical properties of the building envelope and the efficiency of the heating system. In both modelling approaches generalisations are made about the internal temperatures of dwellings. In top-down methods, internal temperatures are used to calibrate model estimates and adjust estimated energy consumption to match aggregate demand [20]. In bottom-up methods internal temperature is generally assumed constant across multiple dwellings or similarly adjusted as a function of the physical properties of the building ignoring completely the effect that different behaviours may have on energy use (BREDEM[2] [21]). Both approaches therefore miss an important opportunity to capture human behaviour through the decisions of individuals that are known to affect heating profiles and mean internal temperatures.

There have been several other important contributions that add to our knowledge of how people interact with home energy systems. Contrary to popular belief, Shipworth et al. [22] show that heating controls may not reduce average living room temperatures or the duration of operation. Regulations, policies and programmes that assume the addition of controls will reduce energy consumption may therefore need to be revised. The impact that smart meters will have on reducing energy and emissions is also controversial. Darby [23] maintains there is little evidence to suggest that smart meters will automatically lead to a dramatic reduction in energy demand. Instead she calls for increased focus on overall demand reduction (rather than peak electricity demand reduction), improvements to the ergonomic design of customer interfaces and on guiding occupants towards appropriate action through feedback, narrative and support for providing the best opportunities to reduce demand.

1.2 The problem with existing building stock models

Top-down models assume a single mean internal temperature for all dwellings in the building stock [24–26] while the remaining models (including BREDEM) attempt to exogenously calculate internal temperature as a function of occupancy, building fabric and technology [21,27,28]. Surprisingly, none of the building stock models developed for use in the UK include internal temperature estimates for temporal resolutions of less than one month. As a result internal temperature is averaged over long periods losing important information about the effect of external temperatures on different heating profiles. Without detailed information on the day to day temperature differences from a heterogeneous building stock it is difficult to set targeted energy policy that correctly accounts for the influence of behaviour. For example, the temperature profile of dwellings occupied by retirees will have very different energy and temperature requirements than a working couple or a busy family. As smart grid technologies become increasingly prevalent, modelling the peaks and troughs will become important for managing the dynamic loads across the network. For peak demand in electricity, the unit of measure is minutes or seconds but for gas it is usually measured in days and hours. Importantly, it is possible to predict peaks in aggregate gas demand using this model. Furthermore, improved understanding of such dynamics will help develop new strategies for reducing CO_2 emissions. Building stock models that utilise temperature data at finer temporal resolutions will be much more adept at

[2] Building Research Establishment Domestic Energy Model (BREDEM) is the foundational building model used for assessing domestic buildings in the UK. It is also used as the basic calculation methodology for SAP and RdSAP.

predicting energy demand and therefore will be able to provide better insight for future policy.

It is now well recognised that internal temperature remains a key determinant for explaining overall home heating energy demand [29]. It is therefore of some concern that internal temperatures are one of the least understood [30] and most generalised variables for modelling domestic energy consumption. All other factors being equal, home heating energy demand is shown to be most affected by changes to internal temperature [27,29]. In a recent study by Cheng and Steemers [27] it is shown that CO_2 emissions are most highly sensitive to internal temperature ($\sigma_{ij} = 1.55$) meaning that a 1% rise in mean internal temperature leads to a 1.55% increase in CO_2 emissions. The same result was found by Firth et al [29] where the length of the daily heating period had the second highest sensitivity ($\sigma_{ij} = 0.62$) and external temperatures the third highest sensitivity ($\sigma_{ij} = -0.58$). Although such models are useful as they provide additional insight into domestic energy demand, a shortcoming is that they do not use empirical data and instead estimate internal temperatures using thermodynamic heat balance equations similar to those employed within BREDEM. Energy demand estimations made with such models are known to have significant discordance with actual energy consumption [31].

Firth et al. [29] estimate internal temperatures using the standard BREDEM steady-state physical equation. In this method an algorithm is employed to estimate monthly internal temperature from an iterative feedback process. First a mean internal temperature of 21°C is assumed throughout the building from which the energy lost through building fabric is calculated using the building heat loss parameter and mean external temperature. The heat loss parameter is calculated from building fabric U-values, infiltration rates and internal heat gains. Because overall energy loss, external temperature and thermal mass of the building are known *a priori*, it is then possible to re-estimate the mean internal temperature of the building. This process is repeated until internal temperature reaches equilibrium. This method is defective in several important respects. First, it ignores human behaviour and thus temperature fluctuations caused by people do not feature at all in the estimation. Secondly, the temperature estimates are not based on empirical temperature readings from the dwelling; rather, they are estimated theoretically from a set of thermodynamic equations. Thirdly, there is no re-evaluation or verification that the temperature estimates used and predicted by the engineering model are representative. Finally, as monthly mean internal temperatures are estimated from building thermodynamics, important information about the daily fluctuations of external temperatures are neglected and averaged out over long periods. Such fluctuations and extremes of external temperature readings are important because they act as triggers to occupants who may change their behaviour due to cold and hot weather events. For example, an early winter cold snap may cause occupants to switch on heating systems much earlier in the heating season than expected, putting increased load on energy networks. Predicting the magnitude and duration of such events is extremely valuable for predicting loads on national electricity and gas networks and for meeting peak demands.

Aside from engineering based approaches statistical or regression based methods can also be used to model energy consumption. For example, Summerfield et al [32] carried out a follow-up study on the 1990 Milton Keynes Energy Performance Dataset (MKEP). In this study 14 of the original 29 dwellings agreed to participate. All dwellings were centrally heated with gas. A regression model was developed that used mean daily external temperature as a predictor of mean internal temperature as well as daily gas and electricity consumption. The results focused on a longitudinal analysis of dwellings between 1990 and 2005. From this small sample a simple bivariate regression model was developed. Due to the small sample size the model prohibits the prediction of internal temperatures for the building stock more generally, but does provide guidance for conducting similar types of analysis. Several other studies have used regression based statistical methods in the analysis of buildings [33,34]. However, none of these earlier studies managed to extend their analyses to utilise the much more powerful statistical properties of panel based methods as they are used in this paper.

Three prominent UK physically based building stock models use BREDEM as the core calculation procedure [22]. These are the UK Domestic Carbon Model (UKDCM) [35]; Johnston's model [36]; and the DeCarb model [30]. Within the descriptions of these models, there is no suggestion that they deviate from BREDEM's standard assumptions or default calculation procedures for estimating internal temperature and heating season duration. All models that adopt standard BREDEM assumptions inherently ignore the effects of human behaviour on energy consumption. Disturbingly these models are still actively used in the development of national policy to curb emissions, improve fuel poverty and predict future trends in domestic energy demand. If emissions reductions are going to be taken seriously, then these models need to actively include the behaviour of individuals as a central component of the energy demand equation.

2 Contribution

A dwelling level temperature model that is capable of predicting internal temperature including the influence of human behaviour will be a useful tool and benefit many existing building stock models. This research will therefore quantify the behavioural, social and demographic properties associated with a building and its occupants and determine the influence of these factors on internal temperature. Benefiting this model is capability to predict internal temperature at much higher temporal resolution than what is presently used by other stock models and is therefore able to predict the variability of internal temperatures as external temperatures fluctuate on a daily basis. Importantly the model can also be used to quantify the rebound effect at the individual building level.

This paper therefore offers several important contributions to this research area:

i) It represents the first known time that a panel model has been used to predict mean internal temperatures from a large sample of heterogeneous dwellings.

ii) It presents a novel method for including social and behavioural variables and how these factors influence internal temperature over a heterogeneous building stock.

iii) It offers a practical solution for energy demand modellers wishing to incorporate improved estimates of mean daily internal temperatures into bottom up models.

iv) It allows statistical inferences to be made about different physical, behavioural, socio-demographic and technical factors from a heterogeneous building stock and the proportion of variance that these different factors contribute towards explaining internal temperature.

3 Comparison of relevant data sources

With approximately 22 million heterogeneous dwellings spread across the UK, each dwelling has a unique energy profile due to its own set of physical properties, climatic conditions and behavioural characteristics of occupants. Built form may vary by date of construction, building typology, floor area, type of construction material and quality of workmanship. Energy systems within dwellings also vary markedly with differences between heating systems, fuel types and efficiency levels. The behavioural qualities of occupants range by socio-demographics, income levels, age and family type [29]. Although dwelling set-point temperatures maybe similar amongst dwellings (e.g. 21°C) there may be important differences in heating duration that result in a large divergence in mean daily internal temperatures. In order to capture the complexities inherent within the residential building stock, it is necessary to have a dataset that contains as much information as possible on the many factors that are known to explain energy demand.

Concerning internal temperatures, National surveys such as the 1996 English House Condition Survey (EHCS) [37] contain spot temperature readings taken on the day of the survey and therefore, cannot be used for any meaningful analysis over time, and certainly not for predicting internal temperature profiles. Other studies have either focused on specific socio-demographic groups within society or specific geographic areas thus limiting the applicability of temperature readings to be used to represent internal temperatures for the national building stock [38–40]. Thermal comfort models such as PMV [41] and adaptive models [42] are developed for engineers and architects for the design of buildings and therefore do not generally consider the temperature requirements and profiles of different occupants. Aside from the dataset used in this study, the most recent geographically comprehensive and nationally representative survey of internal temperature measurements was completed by Hunt and Gidman [43] between February and March in 1978. A total of

1000 households participated in the survey with spot temperature measurements recorded in all rooms of the dwelling. As only spot measurements were taken at the time of the survey, it is not possible to know the specific temperature profiles for each of the dwellings, but the large sample of homes does provide some indication for mean internal temperatures across England. From this study the mean internal temperature in the living room was 18.3°C ($p<0.001$) and for the main bedroom it was 15.2°C ($p<0.001$). Hunt showed that the mean of all dwelling temperatures was most correlated with the landing or stairwell temperature ($r=0.96$), followed closely by the bedrooms ($r=0.94$).

The use of bottom-up building physics models to estimate internal temperatures and energy consumption stems from a paucity of empirical data, and in particular, inadequate samples of high resolution internal temperature readings. In light of these shortcomings McMichael [44] completed a comprehensive review to catalogue all the relevant data sources and their potential for being used in understanding the relationship between energy consumption, buildings and behaviour. McMichael's (2011) literature search involved consulting numerous experts in the field, literature reviews of other grants and publications as well as searching of online data archives hosted by the UK government such as the UK Data Archive. Some forty-four different data-sources were consulted, with each dataset containing unique information applicable to modelling and understanding building energy consumption. The overall conclusion of this data survey was that the CARB-HES dataset was the only data source to contain all the necessary data (including internal temperature readings) in a nationally representative sample of dwellings capable of modelling the complexities inherent in the UK national building stock.

3.1 Data collection

Crucial to estimating and modelling human behaviour as it pertains to residential energy consumption is securing sufficient data about the social and behavioural characteristics of the population being studied. It is therefore necessary to have measureable and quantifiable parameters that are able to relate the socio-demographic and behavioural properties of people to the energy consumption of the dwelling being studied. One possible method to couple the latent property of 'human behaviour' to dwelling energy consumption is through the intermediary variable of internal temperature. Defining internal temperature in this way introduces several problems. If daily internal temperatures are to reflect human behaviour accurately, they must be of sufficiently high temporal resolution so that important distinctions across multiple dwellings will not be averaged out over long time periods. Moreover, internal temperature is both a function of human behaviour and the physical properties of the building, thus it is important to include controls for as many significant variables as possible in the analysis.

The model developed uses the CARB-HES dataset collected between July 2007 and February 2008. Households who participated in the survey were randomly selected from a stratified sample drawn from a postcode address file for England. To ensure a good geographic and socio-demographic spread, post codes were stratified by Government office region and socio-economic class. Out of the 1134 addresses selected a total 427 households opted to participate in the study. Of those households 390 agreed to house at least one temperature sensor, but some households returned their sensors early, or withdrew from the study, or moved house; some sensors were faulty or could not be linked to a household, or the data could not be retrieved from them. Data was retrieved from sensors provided by 280 households, 266 of which had both bedroom and living room data. Occupants from each household were asked to give face-face interviews and answered structured questions about their homes' built-form, heating system, heating practices and socio-demographics. During the interview occupants were asked if they would be willing to accommodate temperature sensors in their living room and master bedroom [22]. Having two temperature loggers for each dwelling was useful as it allowed suspected temperature logger errors (due to incorrect placement or hardware error) to be checked and verified against the second temperature logger. This also allowed for the examination of zoning within a dwelling and to test the accuracy of standard BREDEM assumptions.

The survey was designed for the CaRB consortium by M. Shipworth with sampling and face-to-face interviews conducted by the National Centre for Social Research (NatCen). A wide range of physical characteristics for each building were collected as well as many socio-demographic and behavioural attributes of the occupants. Internal temperatures were recorded in 266 dwellings using HOBO UA 001-08[3] sensors which are small, unobtrusive and silent. Participants were instructed to place the sensor on a shelf or other surface between knee and head height away from any heat sources (such as radiators) and away from direct sunlight. The sensors are self contained data loggers and the information was only retrieved once the study had been completed. Temperature recordings were taken at 45 minute intervals between 22 July 2007 and 3 February 2008. This period was chosen as it spreads across different heating seasons and allows for a sufficiently long monitoring period whilst still capturing short term variations in temperature. The mean temperature over each 45 minute period was recorded at a resolution of 0.1°C. The HOBO temperature sensors had a reported accuracy of ±0.47°C at 25°C. Calibration measurements were taken on each sensor before they were installed in the home and used to correct the readings once the measurements had been downloaded. The calibration error from all sensors was found to be minimal $\left(\bar{x} = 0.19, \sigma = 0.11\right)$. The survey represents the first nationally representative sample to combine high temporal resolution temperature readings with both physical and socio-demographic characteristics of the dwelling. A dataset containing several hundred dwellings

[3] www.tempcon.co.uk/

each with temperature readings taken at 45 minute intervals over a period of 6 months generates a very large dataset with approximately 1.5 million temperature spot measurements. Datasets this large require specialist software packages for data handling and post-processing. In this study, MS Access, SPSS, STATA and MatLab were all used in the management of data. Dataset files were imported as MDB files into Microsoft Access and then converted to DBF files before they could be imported and processed in SPSS, STATA and Matlab for further statistical analysis.

Although the CARB-HES dataset covers a comprehensive array of social, behavioural and physical characteristics, external temperatures over the period of the study were not included in the original survey. In order to overcome this deficiency, an external temperature dataset was created containing average external daily temperature readings for each of the nine government office regions in England. Finer geographic-spatial resolution down to the local authority level was not necessary as doing so did not add significantly more variation than what was already captured at the regional level. The dataset was downloaded and created with permission from the British Atmospheric Data centre (BADC) [45]. The regional external temperature dataset is available for public use with appropriate recognition and permission from BADC [46]. Figure 1 shows the mean daily external temperatures for each Government Office region in England from 1st August 2007 to the 31st January 2008.

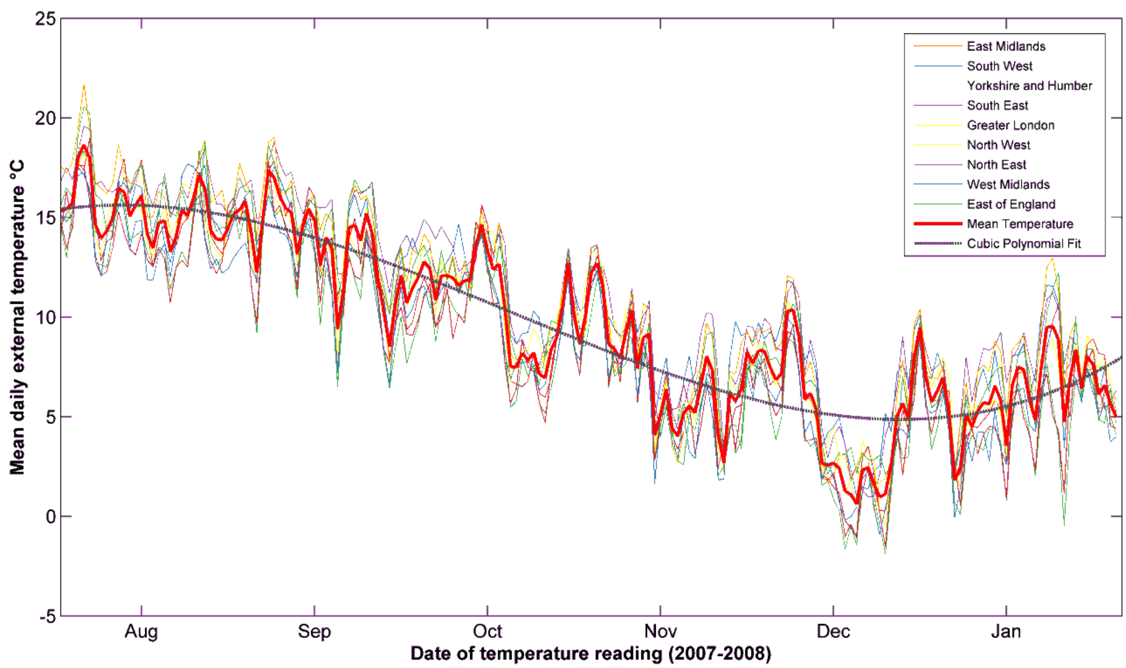

Figure 1: Mean external temperatures by Government office region (Aug 2007- Jan 2008)

$$T = 8.8\times10^{-6} x^3 - 0.002x^2 + 0.045x + 15 \tag{1.1}$$

Equation (1.1) governs the polynomial fit of mean daily external temperature and shows the typical sinusoidal relationship usually associated with external temperatures.

4 Development of the statistical model

Several statistical procedures were reviewed for their appropriateness in modelling time-series data. Well developed panel data methods allow cross-sectional and time-series data to be modelled without incurring data reduction penalties due to averaging of the temperature readings over time or across dwellings. Panel data methods thus have several important benefits over other statistical methods.

i) they produce more informative results because they contain more degrees of freedom thus making the estimates more efficient than standard cross-sectional methods;

ii) they allow the study of subject level dynamics by separating or controlling for different cohort effects over time;

iii) they provide additional information on the time ordering of events;

iv) they make it possible to capture variation occurring over time or space and how these two effects vary simultaneously;

v) they allow for the control of individual unobserved heterogeneity and contemporaneous correlation across a sample.

Given these advantages it is no surprise that panel methods have become widely used in many quantitative research disciplines. Although panel-data approaches provide many benefits for substantive research, the method does introduce several complications that must be overcome before robust statistical inferences can be made or the model used to make credible predictions. A typical problem arising from the use of panel data methods is that they often violate standard OLS assumptions about the error process[4] (see Equations 1.1 – 1.3) [47]. In typical regression methods it is frequently assumed that errors are either normal or independently identically distributed (IID). In panel data this assumption is often violated due to the longitudinal nature of recordings (i.e. measurements over time are correlated). Although it is common to assume that errors are not correlated with regressors over a cross-section of records, it is almost never the case that errors are uncorrelated within an entity over time, thus giving way to serial correlation. In addition, errors in panel data tend to be heteroskedastic such that they have changing variances over time and over panels. Panel data methods thus require the use of much more sophisticated estimation methods than typical cross-sectional or time-series dependent analyses to allow for the additional complications that arise.

[4] For OLS to be optimal it is necessary that all errors have the same variance (homoskedasticity) and that all the errors are independent of each other.

Because panel methods are an extension of standard regression techniques they are still dependent on many of the same assumptions:

i) $E(\varepsilon_i \mid x_i) = 0$ (exogeneity of regressors) (1.2)

ii) $E\left(\varepsilon_i^2 \mid x_i\right) = \sigma^2$ (conditional homoskedasticity) (1.3)

iii) $E\left(\varepsilon_i \varepsilon_j \mid x_i x_j\right) = 0,\ i \neq j$ (conditionally uncorrelated correlations) (1.4)

Assumption 1 is essential for consistent estimation of β coefficients and implies that the conditional mean is linear and all relevant variables have been included in the regression. It is however possible to relax this assumption in some specific circumstances [48]. If all three assumptions are met then the OLS estimator is fully efficient. If in addition the errors are normally distributed then t-statistics are also exactly t-distributed. If Assumptions *ii)* and *iii)* cannot be met then OLS is no longer efficient and estimation using other methods is possible and generally more efficient.

Specially developed statistical techniques capture the variations across individuals whilst also allowing for variations that occur over time. Several practical considerations arise when conducting panel data analysis. Estimator consistency requires that the sample-selection process does not lead to errors being correlated with the regressors. However, when using panel-data, it is very likely that model standard errors are correlated with regressors over time. It is also plausible that error correlation exists between cross-sections of the sample. Special statistical techniques have been devised to ameliorate both of these situations. Regardless of the assumptions being made, it is typically necessary to make corrections to OLS estimations for panel data (e.g. Panel Corrected Standard Errors). In addition, it is sometimes possible to improve the efficiency of the model by using other estimators such as generalised leased squares (GLS).

When performing panel analysis, regression coefficient identification depends on the type of regressors being specified. For example, some regressors are time-invariant and thus affect decisions about the type of model that can be used. Moreover, it is also possible that some regressors covary over time and also by cross-section. Many econometric techniques therefore recommend the use of either fixed effects models or random effects models for conducting panel data analysis which depends on the structure of variables included in the model.

First, lets consider Pooled Regression (PR), also known as the population averaged model which is also the simplest approach for modelling panel datasets. If standard OLS assumptions are met (i.e. zero conditional mean of errors, homoskedasticity, independence across observations and strict exogeneity of covariates) then OLS techniques are efficient and can reliably be used to estimate parameters [49]. However, because we are using longitudinal data it is unreasonable to assume that errors are not correlated over time, thus ruling out pooled regression as an estimation technique.

Second, let's consider the Fixed Effects (FE) model. Like first differencing methods, FE methods use a transformation to remove any unobserved effects prior to estimation. In this method time invariant explanatory variables are removed [50]. In FE models it is not possible to draw inferences or predictions from time-invariant effects as such effects are averaged out and controlled for as part of the transformation process [51]. In FE models the researcher is primarily concerned with understanding the effect of different covariates as they vary with time. Any time-invariant cross-sectional heterogeneity (and unobserved time-invariant heterogeneity) therefore drops out during the differencing transformation. The result is a model with different estimates for model intercepts, ν_i across the panel but with each panel having the same slope. Time-invariant effects are of acute interest for this model[5]. As FE models cannot estimate time-invariant effects, the FE model was rejected for use in developing this model. For completeness, the FE estimator is typically given by Equation (1.5).

$$y_{it} = \beta_1 x_{it} + \nu_i + \varepsilon_{it} \tag{1.5}$$

In Equation (1.5) for FE estimation, y_{it} is the predicted variable for entity, i, at time, t, β_1 is the common slope parameter, x_{it} is the covariate, ν_i is the subject specific error and ε_{it} is the idiosyncratic error.

Similar to FE analysis the Least Squares Dummy Variable (LSDV) method includes dummy variables for every dwelling in the dataset. The LSDV method is generally not advised for long datasets when the number of cross-sectional variables in the data is close to the number of time-periods as this substantially reduces the degrees of freedom available to the model. This method was therefore also rejected on the basis that it would require 184 additional dummy variables representing each time period.

For Random Effects (RE) models using standard OLS assumptions, it is possible to include time invariant covariates. In RE models a constant intercept is added to Equation (1.5). The

[5] Time invariant effects are factors that do not change over time, such as how many occupants live in the household or whether there is temperature control inside the dwelling.

individual specific error, ν_i, is assumed IID and assumes any unobserved effects are uncorrelated with all explanatory variables [i.e. $\mathrm{Cov}(x_{itj}, a_i) = 0$]. In addition, $\nu_i \sim IID(0,\sigma_\mu^2)$, $\varepsilon_{it} \sim IID(0,\sigma_\mu^2)$ and ν_i are independent of ε_{it}. The random effects model is an appropriate specification if the number of observations (dwellings), N, is large [52]. Also, as the number of time periods, $X \to \infty$, the differences between FE and RE disappear. Thus for a RE model Equation (1.5) becomes:

$$y_{it} = \alpha + \beta_1 x_{it} + \nu_i + \varepsilon_{it} \tag{1.6}$$

When data are longitudinal, positive serial correlation in the error term can be substantial, and as OLS standard errors ignore this correlation the estimators predicted by OLS will be incorrect [53]. Both RE and FE models that use OLS are best suited for short panels where N is large and X is small and errors are random. For a longer panel where N is large and the number of time periods: $X \to \infty$, much richer models can be specified using the more efficient General Least Squares (GLS) or Panel Corrected Standard Errors (PCSE). These estimators are also able to control for serial correlation [48].

After ruling out the OLS estimator, FE, LSDV and PR methods, the model was developed using RE and tested using a number of different estimators that allow for longitudinal serial correlation when errors are assumed not IID. The GLS estimator, PCSE estimator and XTSCC estimation methods allow the errors $(\nu_i, \varepsilon_{it})$ to be correlated over *i*, allow autoregressive correlation of ε_{it} over *t*, and allow ε_{it} to be heteroskedastic [54,55]. The GLS estimator as originally proposed by Parks and Kmenta involves complex matrix algebra to be solved [54,55]. However, modern econometric software packages now allow this step to be completed automatically. For a discussion on the benefits and disadvantages of GLS over other procedures please refer to the following text books [51,56]

The PCSE estimator uses OLS and by default assumes contemporaneous correlation between panels. Beck and Katz [57,58] show that the overconfidence in standard errors makes the Parks-Kmenta method unusable in situations when $N < X$ and therefore they propose a new method. As already stated, if errors do not meet the standard OLS assumptions, the OLS estimates of parameter coefficients will be consistent but inefficient. Beck and Katz thus propose to retain the OLS parameter estimates but replace the OLS standard errors with Panel Corrected Standard Errors (PCSE) that take into account the heteroskedasticity and contemporaneous correlation between errors. As already noted the GLS and PCSE estimators offer some unique features, including flexibility to control for different assumptions concerning the distribution of standard errors [59]. However, if the model is correctly specified then the GLS estimator is generally more efficient than PCSE [48]. Thus, to summarise, the error structure within panels for both GLS and PCSE estimators may be specified as having:

i) no autocorrelation within panels; or

ii) AR1 autocorrelation within panels where the coefficient of autocorrelation is constant across all panels, or,

iii) AR1 autocorrelation within panels where the coefficient of autocorrelation is panel-specific.

The errors structure between panels is specified slightly differently for GLS and PCSE models. For GLS models the between panel correlation can be specified as:

i) homoskedastic with no contemporaneous correlation, otherwise known as IID,

ii) heteroskedastic with no contemporaneous correlation, or,

iii) heteroskedastic with contemporaneous correlation when $T > N$

For PCSE estimation the structure of errors between panels is specified as being:

i) heteroskesdatic with contemporaneous correlation between panels (default)

ii) heteroskesdastic with no contemporaneous correlation between panels or,

iii) independent errors between panels with a single disturbance variance common to all panels.

When the error, ε_{it}, between panels are assumed to be IID using the GLS estimator, the pooled OLS estimator is obtained. When panels are assumed heteroskesdastic, ε_{it}^2, is specified as independent with variance $E(\varepsilon_{it}^2) = \sigma_i^2$ and can be different for each dwelling. Because there are many measurements for each dwelling over time, σ_i^2 can be consistently estimated [48]. When, $X > N$, correlation across panels can be allowed for.

A third procedure developed by Driscoll and Kraay [60] generalises the PCSE method. This was implemented in STATA by Hoechle [61] to obtain Newey-West [62] standard errors. Correlation of errors between panels (spatial correlation) is assumed while auto-correlation within panels can be assumed to be of the general-form rather than AR1. The general procedure determines the most efficient number of lags, *m*, for the model being estimated.

Several restrictions are placed on estimating these different models. If the GLS estimator is used with autocorrelation then time-series data must be equally spaced in time. If cross-sectional correlation is also assumed then the panel must be balanced. A model that assumes a common autocorrelation value across panels is only reasonable when the individual panel level correlations are almost equal and the time-series is short [59]. As the time series used in this analysis is represented by 184 unique days, the panel is considered too long to make this assumption and thus we assume that each panel has unique autoregressive properties.

4.1 Description of dataset

In Figure 2 the mean daily internal temperature distributions[6] for the living room and bedroom can be compared with the distribution for mean daily external temperature[7]. Figure 3 represents a binned scatter plot of mean daily internal temperature vs. mean daily external temperature by dwelling and by day. The large hollow circles represent a concentration of observations. The plot shows large variation between dwelling internal and external temperatures. The scatter plot also shows bimodality in external temperatures as also shown in the histogram plot (Figure 2).

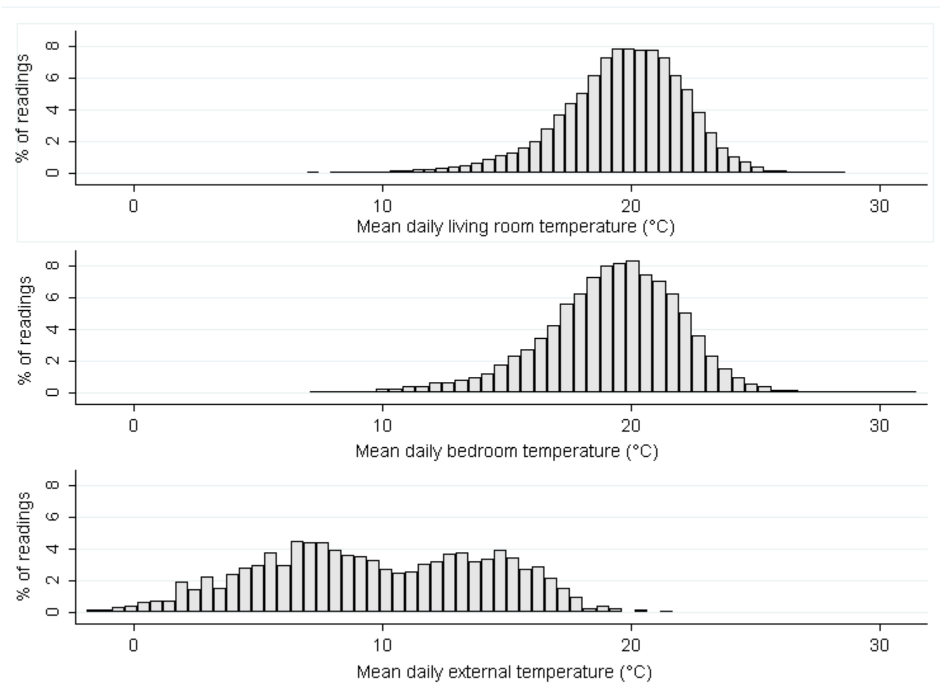

Figure 2: Internal and external temperature distributions

[6] Mean internal temperatures are calculated as the arithmetic mean of the bedroom and living room temperature for each dwelling over 24 hours.
[7] Mean external temperature is calculated for each government office region in England and is the arithmetic mean daily external temperature for all weather stations within each government office region.

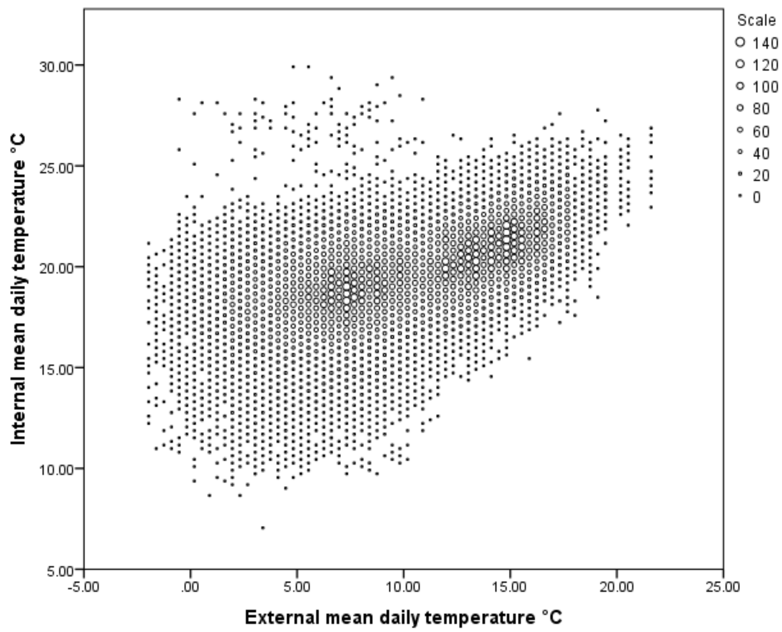

Figure 3: Internal temperature plotted against external temperature

A binned scatter plot of mean internal daily temperature readings for each dwelling is given in Figure 4. Several observations can be made from this plot. First, as external temperatures drop, so do mean internal temperatures. Second, internal temperatures are widely dispersed around the mean with dispersal increasing in the heating season. Interestingly, it appears several households heat their homes to much higher temperatures in winter than in summer. At the colder end of the spectrum some homes do not even appear to be heated, with recorded temperatures well below 10°C. This possibly suggests these homes are either unheated or unoccupied. All observations were retained for subsequent analyses.

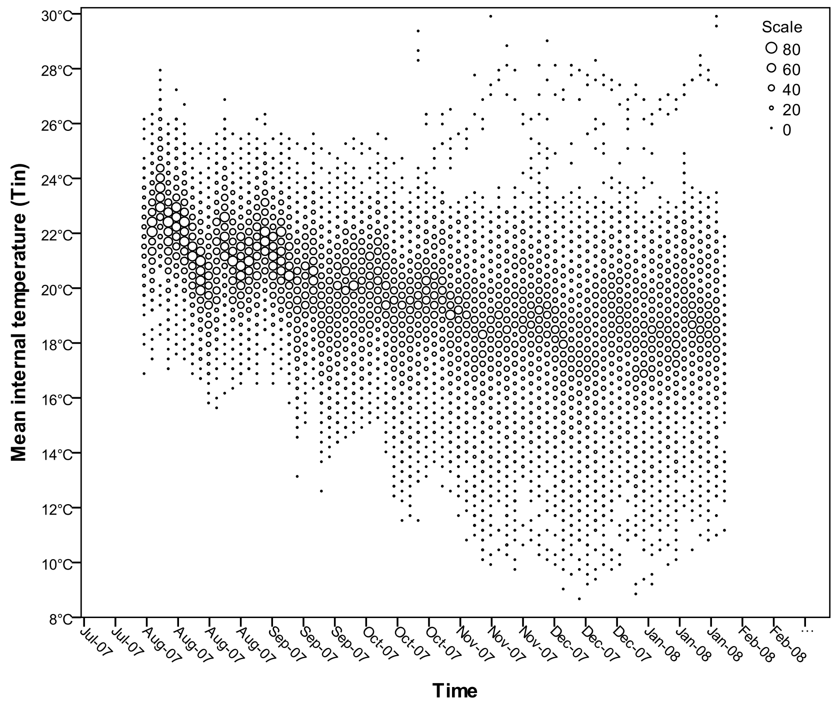

Figure 4: Temperature recordings

Comparison of the CARB-HES dataset with the English House Condition Survey (EHCS 2007) shows the CARB-HES dataset represents the English housing stock relatively well.

Table 1: Comparing the CARB-HES dataset with national estimates

Variable name	CARB-HES Survey (%)	EHCS 2007 (%)[1]
Tenure type		
Owner occupied	303 (71%)	7710 (71%)
Privately rented	46 (11%)	2,161 (12%)
Local Authority	39 (9%)	3,501 (9%)
Housing Association	38 (9%)	2,232 (8%)
Dwelling type		
Terraced	97 (23%)	4,775 (28%)
Semi-detached	125 (29%)	4,183 (28%)
Bungalow or detached	123 (29%)	3,661 (27%)
Flats	82 (19%)	3,598 (17%)
Dwelling Age		
Pre 1919	62 (15%)	3014 (21%)
1919 – 1944	79 (18%)	2,755 (17%)
1945 – 1964	98 (23%)	3,868 (20%)
1965 – 1980	96 (22%)	3,855 (22%)
Post 1980	90 (21%)	2,725 (20%)
Total number of households in survey	427	15,604

1. Weighted sample taken from the English House Condition Survey 2007-08 [63]

5 The model

The aim of the model is two-fold. Firstly it can be used for the development of statistical inference and therefore is able to improve our understanding of the relative importance of different variables in explaining internal dwelling temperatures in England. Secondly, the model can be used to predict internal temperature at the dwelling level and is therefore implementable by any bottom-up engineering or statistical building stock model. Most building stock models would benefit from more robust estimates of internal dwelling temperature. Thus the model is able to provide, within known uncertainty bounds, an estimate of the internal temperature for any typical dwelling in England for any given day of the year based on the dataset described. The variables finally chosen for testing the model were selected for their known effect on mean internal temperatures. The variables used by the model are separated into three distinct groupings:

i) Intransmutable variables (variables that cannot be influenced or changed to reduce energy consumption) such as external temperatures and geographic location;

ii) Behavioural and socio-demographic variables such as occupancy rates, thermostat settings and heating duration hours; and,

iii) Variables that represent the physical characteristics of the building.

The general form of the temperature model can therefore be given by Equation (1.7) …

$$Tin_{it} = \alpha + \boldsymbol{\Gamma}_{it}\boldsymbol{\beta}_1 + \boldsymbol{\Psi}_{it}\boldsymbol{\beta}_2 + \boldsymbol{\Theta}_{it}\boldsymbol{\beta}_3 + \left(\nu_i + \varepsilon_{it}\right); \qquad \begin{matrix} i = 1, ..., N \\ t = 1, ..., X \end{matrix} \tag{1.7}$$

In Equation (1.7) Tin_{it} is the mean internal daily temperature associated with dwelling, i, at time period t and is the mean of the main bedroom and living room temperature over 24 hours; $\boldsymbol{\Gamma}_{it}$ represents a matrix of intransmutable variables with a complementary array of parameter coefficients, $\boldsymbol{\beta}_1$; $\boldsymbol{\Psi}_{it}$, represents a matrix of behavioural and socio-demographic variables and $\boldsymbol{\beta}_2$ is the corresponding array of parameter coefficients for each behavioural characteristic; $\boldsymbol{\Theta}_{it}$, is a matrix of physical building characteristics with a corresponding array, $\boldsymbol{\beta}_3$, of coefficient estimates; α is a constant intercept term; ν_i, is the between entity error; ε_{it}, is the idiosyncratic error term that varies for each dwelling and each time period. Table 2 gives important descriptive statistics for the data.

Although the model was generated using mean daily temperature data, there is no reason the model can not be used to predict average monthly or weekly internal temperatures if the corresponding mean external temperatures over the month or season in question and other variables are known *a priori*. If mean monthly external temperatures are used instead of mean daily temperatures, then the model will predict the mean internal monthly temperature for the dwelling.

6 Description of model

This dataset is unbalanced and contains 42,723 data-points from 266 separate panels (dwellings) over 184 time periods (days). Relative to other panel models, the data used for this analysis is described as both long and wide as it has both large N and large X . This is beneficial when conducting panel data analyses because the total number of data-points is very large and therefore the restrictions usually placed on models to maintain large degrees of freedom (*dof*) is not a limiting factor. Parsimony is however still highly valued. Parsimony simply requires that when two models have the same explanatory power or predictability, then the simpler version of the model is chosen in preference to the more complicated one.

6.1 Description of model variables

Dichotomous or dummy variables were created to represent nominal unordered categorical variables. Many of the response variables also contain multiple unordered categories. The dummy variable trap was avoided by creating dummy variables for each response category with the exception of the comparison category [64]. The comparison category is the category that all other dummy variables are compared against and occurs when all dummy variables from that category are equal to zero. Therefore, if a response variable has four categories then three dummy variables are chosen for three of the categories and the fourth category is assigned as the comparison category. In this model there are four response categories that represent *Geographic Region*, *Age of Occupants*, *Ownership type* and *House typology*.

Average daily internal temperature, Tin_{it} , is the mean daily internal temperature and is calculated as the average of the bedroom and living room temperature over 24 hours. The mean daily temperature is calculated from 64 temperature readings taken at 45 minute intervals from each dwelling, i , for each day, t , from the 1st August 2007 to the 31st January 2008. Average daily external temperature, $Text_{it}$, is the regional external temperature on day, t , for the government office region where the dwelling is located. Regional dummies are included for each of the nine government office regions to control for any unobserved heterogeneity at the regional level that may affect internal temperatures.

Table 2: Descriptive statistics used in the analysis [1,2]

Variable description	name	type	Mean (%)[3]	median	std.dev	min	max
Mean internal daily temp	$Tint_{it}$	Scale	19.61	19.64	2.47	7.05	29.92

Intransmutable Variables, Γ_{it}							
Mean external daily temp	*Text*	Scale	9.71	9.43	4.59	-1.89	21.68
Geographic location							
(A) London	*LON*	Dummy	(8%)	-	-	0	1
(A) North East	*NE*	Dummy	(6%)	-	-	0	1
(A) Yorkshire and Humberside	*YORK*	Dummy	(9%)	-	-	0	1
(A) North West	*NW*	Dummy	(15%)	-	-	0	1
(A) East Midlands	*EM*	Dummy	(7%)	-	-	0	1
(A) West Midlands	*WM*	Dummy	(16%)	-	-	0	1
(A) South West	*SW*	Dummy	(15%)	-	-	0	1
(A) East of England	*EE*	Dummy	(13%)	-	-	0	1
(A) South East	*SE*	Dummy	(10%)	-	-	0	1
Behavioural and socio-demographic variables, Ψ_{it}							
Room thermostat exists	*T_Stat*	Dummy	(49%)	-	-	0	1
Thermostat Setting	*T_Set*	Scale	19.19	19.4	3.40	0	32
Thermostatic radiator valve only (TRV)	*TRV*	Dummy	(22%)	-	-	0	1
Central heating hours reported	*CH_Hours*	Scale	9.84	9	5.30	1	24
Regular heating pattern	*Reg_Pat*	Dummy	(88%)	-	-	0	1
Automatic Timer	*Auto_Timer*	Dummy	(60%)	-	-	0	1
Household Size	*HH_Size*	Categorical	2.3	2	1.15	1	7
Household Income	*HH_Income*	Scale	31,570	23,833	24,191	1,940	137,500
Age of occupants							
Child aged < 5	*Child<5*	Dummy	(8%)	-	-	0	1
Number of children < 18	*Children<18*	Categorical	0.41	0	0.81	0	4
(B) All occupants aged under 60	*Age<60*	Dummy	(53%)	-	-	0	1
(B) Oldest occupant aged 60-64	*Age60-64*	Dummy	(14%)	-	-	0	1
(B) Oldest occupant 65-74	*Age64-74*	Dummy	(20%)	-	-	0	1
(B) Oldest occupant > 74	*Age>74*	Dummy	(13%)	-	-	0	1
Tenure type							
(C) Owner occupier	*Owner*	Dummy	(82%)	-	-	0	1
(C) Privately Rented	*Rented*	Dummy	(5%)	-	-	0	1
(C) Council tenant	*Council*	Dummy	(8%)	-	-	0	1
(C) Housing Association or RSL	*H_Assoc*	Dummy	(5%)	-	-	0	1
Weekend Properties							
Weekend heat same as weekday	*WE_Same*	Dummy	(77%)	-	-	0	1
Weekend temperature reading	*WE_Temp*	Dummy	(28%)	-	-	0	1
Building efficiency and heating system variables, Θ_{it}							
(D) Detached house	*Detached*	Dummy	(34%)	-	-	0	1
(D) Semi-detached house	*SemiDet*	Dummy	(29%)	-	-	0	1
(D) Terraced house	*Terraced*	Dummy	(23%)	-	-	0	1
(D) Not a house	*NotHouse*	Dummy	(14%)	-	-	0	1
Heating systems							
Gas central heating	*Gas_CH*	Dummy	(84%)	-	-	0	1
Non central heating is used	*Non_CH*	Dummy	(64%)	-	-	0	1
Electricity is main fuel	*Elec_Main*	Dummy	(7%)	-	-	0	1

Gas additional heating in living area	*Gas_OH*	Dummy	(33%)	-	-	0	1
Electricity additional heat in living area	*Elec_OH*	Dummy	(13%)	-	-	0	1
Other additional heating in living area	*Other_OH*	Dummy	(13%0	-	-	0	1
Building efficiency							
Year of building construction	*Build_Age*	Categorical	5.45	5	2.18	1	10
Roof insulation thickness	*Roof_Ins*	Categorical	3.0	4	2.1	0	7
Extent of double glazing	*Dbl_Glz*	Categorical	4.32	5	1.32	1	3
Wall U-Value	*Wall_U*	Scale	1.19	1.18	0.68	0	1

1. Response categories that belonging to a group are given a letter so that is clear that these variables are part of the same group.
2. Variables in bold represent the comparison category and are excluded from the panel model (i.e. all dummy variables in the category are calculated relative to this variable)
3. For dummy variables the mean represents the proportion of the population (in percent) that are represented by that indicator.

The following section describes each of the variables selected for the analysis. We start with a description of different heating control options.

Room thermostat is a dichotomous variable that indicates if a room thermostat is present in the dwelling.

Thermostat setting is the respondent's declared thermostat setting for the dwelling in degrees Celsius and has been grouped into four categories (*Table 3*).

Thermostatic Radiator Valve (TRV) is a dichotomous variable indicating if the only type of temperature control is with thermostatic radiator valves.

Central heating hours reported is a continuous scale variable indicating the average number of central heating hours reported per day over the week including weekends.

Regular heating pattern is a dichotomous variable indicating if the home is heated to regular heating patterns during the winter.

Automatic timer is a dichotomous variable indicating that the home uses an automatic timer to control heating.

There are many socio-demographic factors that contribute to internal temperature. Here we capture household size, household income and occupant age. Several categories are used to describe the *Age of occupants*. A response category of dichotomous variables is used to describe differences amongst the older population (*Age64 – Age74*).

Household size is the number of occupants living in the dwelling at the time of the survey;

Household income is the gross take-home income for the whole household and has been categorised into seven income bands;

Child<5 is a dichotomous variable indicating if any infants under the age of five are present in the dwelling;

Children<18 is a discrete scale variable indicating the number of children under the age of 18 living in the dwelling;

Table 3: Ordered categorical variables for socio-demographic and behavioural properties

Response category	Thermostat setting	Household size	Income groups

Response category	Thermostat setting		Household size		Income groups	
	T_Set		*HH_Size*		*HH_Income*	
	°C	Freq (%)	Occupants	Freq (%)	Income	Freq (%)
0	<18	12.77	-	-	<£5,199	2.58
1	18-20	64.85	1	25.72	£5,200 - £10,399	13.65
2	20-22	13.34	2	41.70	£10,400 - £20,799	26.62
3	>22	9.04	3	15.39	£20,800 - £36,399	26.99
4			4	12.88	£36,400 - £51,999	16.78
5			5	3.45	£52,000 - £94,999	12.49
6			6	0.43	> £95,000	3.88
7			7	0.43		

(A) ***Age<64*** is a dichotomous variable indicating if the oldest person living in the dwelling is under 64 years of age. For this analysis, this will also be the comparison category that other ages are compared against;

(A) Age59-64 is a dichotomous variable that represents if the oldest person living in the dwelling is aged between 59 and 64;

(A) Age64-74 is a dichotomous variable that represents if the oldest person living in the dwelling is aged between 64 and 74;

(A) Age>74 is a dichotomous variable that represents if the oldest person in the dwelling is over 74;

The second response category captures the tenure of the property. Tenure type is represented by an exhaustive list of dichotomous variables with owner-occupiers selected as the comparison category.

(B) ***Owner occupier*** is a dichotomous variable and indicates the dwelling is owned by the occupants;

(B) Privately Rented is a dichotomous variable and indicates the dwelling is privately rented by the occupants;

(B) Council tenant is a dichotomous variable and indicates if the dwelling is leased from the council;

(B) Housing Association is a dichotomous variable and indicates if the occupants rent the property from a housing association or registered social landlord (RSL);

The effect of changes to internal temperatures due to weekends was also controlled.

Weekend heat same as weekday is a dichotomous variable and indicates a positive response to the question: "Do you heat your home the same on the weekend as during the week?";

Weekend temperature reading is a dichotomous variable indicating if the temperature reading was recorded during the weekend;

Although we are primarily interested in drawing inferences from the behavioural variables in regression, it is necessary to include all factors that are known to influence the dependent variable (internal temperature). Therefore several building physics and energy efficiency variables unique to each dwelling were included in this analysis. House typology is the fourth and final exhaustive comparison category of dichotomous variables. A detached house was used as the comparison category.

(C) ***Detached House*** is a dichotomous variable and indicates the dwelling is detached;

(C) Semi-Detached is a dichotomous variable indicating a semi-detached dwelling;

(C) Terraced house is a dichotomous variable indicating a terraced house;

(C) Not a house is a dichotomous variable used to represent flats and apartments or any other building not considered as a stand-alone house.

Several variables were included to represent the type of heating system present in the dwelling, as these may also affect the internal temperature.

Gas Central heating is a dichotomous variable used to represent if the dwelling has gas central heating;

Non central heating is a dichotomous variable used to represent dwellings with non-central heating systems (i.e. wood stove, electric fan heaters etc);

Electricity is main fuel is a dichotomous variable that represents if electricity is the main type of heating fuel;

Additional gas heating in living room is a dichotomous variable used to represent the presence of gas heating in the living room in addition to central heating.

Additional electricity heating in living room is a dichotomous variable used to represent the presence of electric heating in the living room in addition to central heating.

Additional other heating in living room is a dichotomous variable used to represent if the presence of additional other forms of heating in the living room.

Several variables were chosen to represent the overall efficiency of the building fabric. These variables were transformed into ordered categorical variables to capture the large variety of different efficiency levels within the building stock. The different categories chosen for these variables are included in Table 4. Categories were chosen to achieve a good spread of the distribution in different categories.

Year of construction is an ordered categorical variable specifying the year the building was constructed.

Roof insulation thickness is an ordered categorical variable representing the thickness of the roof insulation.

Extent of double glazing is an ordered categorical variable indicating the proportion of double glazing in the dwelling.

Wall U-Value is an ordered categorical variable and represents the average U-Value of external walls.

Table 4: Ordered categorical variables used in model to describe building fabric

Response categories	Year of Construction		Roof insulation thickness		Extent of Double Glazing		Wall U-Value	
	Build_Age		*Roof_Ins*		*Dbl_Glz*		*Wall_U*	
	Age band	**Freq (%)**	**(mm)**	**Freq (%)**	**Fraction**	**Freq (%)**	**$W/m^2.K$**	**Freq (%)**
0	pre 1850	5.6	None	24.46	None	9.76	≤0.4	7.32
1	1850-1899	4.73	0-25	2.58	less than half	5.17%	0.4-0.6	32.74
2	1900-1918	4.31	25-50	8.15	about half	2.56%	0.6-1.6	28.66

Response categories	Year of Construction		Roof insulation thickness		Extent of Double Glazing		Wall U-Value	
3	1919-1944	16.73	50-75	14.57	more than half	7.72%	>1.6	31.28
4	1945-1964	23.65	75-100	27.42	all windows	74.79		
5	1965-1974	15.83	100-150	13.78				
6	1975-1980	9.37	150-200	3.44				
7	1981-1990	10.73	>200	5.59				
8	1991-2001	4.74						
9	2002-2006	4.31						

6.2 Missing values, nonlinearities and variable transformations

Missing values can be problematic if not dealt with correctly. Although it is relatively straightforward to use panel methods when datasets are unbalanced (i.e. some values over time are missing) the problem becomes more serious when cross-sectional, time-invariant variables are missing for some of the panels (dwellings). One standard approach in econometrics is to use listwise deletion of the observation containing the missing variable. This has the negative side-effect of throwing away valuable information and reducing the size of the dataset, leading to less precise estimation and inference. Importantly, it may even lead to sample selection bias for the values that are retained. This was resolved for dummy variables in this analysis by giving a value of one to positive responses and giving a value of zero to negative responses and missing values, and therefore retaining the observation. The widely recognised mean substitution method was applied to scale variables [65]. When mean substitution is used to replace values that are missing completely at random (MCAR) the resulting parameter estimates are unbiased [66]. In a comparative analysis, Donner [67] showed that mean substitution is relatively effective when correlations between variables are low and the proportion of missing cases is fairly high. The main criticism of mean substitution is that it gives no leverage to the replaced values; and when there are substantial missing values it reduces the Pearson correlation coefficient (R^2). The approach therefore implies that the mean substitution does not influence the predicted response [65]. Given the aforementioned problems of missingness as well as the extent and randomness of missingness within the original dataset, mean substitution was employed to replace the missing scale variables before they were categorised.

When using least squares estimates, the Gauss-Markov theorem does not require variables to exhibit univariate normality for the parameter coefficients to be meaningful. However, confidence levels and hypothesis tests will have better statistical properties if the variables do exhibit multivariate normality. It is typical for some distributions, such as *Household Income,* to have non-normal properties. This is shown in Table 2**,** where it is clear that the median of *HH_Income* is very different to the mean suggesting deviation from the normal. Thus to counteract this effect, *HH_Income* was categorised into a discrete number of bins (see Table 3). This has the effect of grouping extreme values situated in the tail ends of the distribution into discrete bins and therefore meeting standard assumptions about the distribution of values. The benefit of using this method over log-transformations is that the final output is directly interpretable and requires no post-transformation of model variables.

A further assumption of regression based estimates is that there is a linear relationship between dependent and independent variables. It is incorrect to assume a direct linear relationship between external and internal temperature. The relationship is nonlinear in this instance because as external temperatures increase, the power of external temperature to explain internal temperature increasingly dominates the equation. Said differently, as external temperatures rise, the need for central heating decreases nonlinearly, until internal temperature at least[8] reaches equilibrium with external temperature and there is no need for central heating at all. This non-linear relationship was allowed for by the inclusion of the square of external temperature within the regression equation.

6.3 Testing procedures

The temperature model described above was estimated using STATA11. STATA11 implements a library of functions for manipulating and estimating panel data using the `xt` family of commands [59]. Several statistical tests were conducted on the panel data before any substantive statistical modelling was undertaken. First the Breusch-Pagan Lagrange Multiplier (LM) test was used to decide if random effects regression was more appropriate than ordinary least squares (OLS) linear regression. The null hypothesis for the LM test is that the variance across dwellings is zero (i.e. no panel effect). This was implemented in STATA by first running the model using the `xtreg` with random effects and then running `xttest0` [68]; χ^2 is then used to compare the two models. The test rejected the null hypothesis that a random effects model was not appropriate. We therefore have evidence that a RE panel model will produce more efficient results than standard regression using OLS.

Panel level auto-correlation was tested using Druckers [69] test procedure within STATA11. The theory behind this test is explained by Wooldridge [56] and is able to identify serial correlation in panel data of the idiosyncratic error term. The only two variables in the model that are not time-invariant (*Text* and *WE_Temp*) were tested for serial correlation. The null for this test procedure was rejected (p<0.001), suggesting that the panel data structure may contain serial correlation. This result was expected as external temperatures are of course correlated over short periods of time (i.e. $corr(Text_n, Text_{n-1}) \neq 0$). Serial correlation in longitudinal panels is not uncommon and can be correctly handled using appropriate statistical techniques as discussed shortly.

[8] Internal temperatures may exceed external temperatures due to internal heat gains (i.e. solar gains) even after heating systems have been switched off.

A Fisher-type test and Levin-Lin-Chu test were completed to test for stationarity within the panels. The Fisher-type test allows hypothesis testing in unbalanced panels while the Levin-Lin-Chu test requires strongly balanced panels [52]. Both tests rejected the null hypothesis that at least one of the panels had a unit root and thus it was concluded that the panels satisfy the condition of non-stationarity implying we may proceed with the panel analysis.

Two further tests were completed to check for heteroskedasticity amongst residuals. The assumption of homoskedasticity across residuals when heteroskedasticity is present results in consistent but inefficient parameter estimates [52]. Also, the standard errors of the estimates may be biased. A modified Wald statistic was used to test groupwise heteroskedasticity in the residuals using `xttest3` after running `xtgls` using the default panels option. The null hypothesis ($H_0 : \sigma_i^2 = \sigma^2$) was rejected, suggesting deviation of the residuals from homoskedasticity. A likelihood ratio test also confirmed this conclusion. The likelihood ratio test requires the model to be tested while assuming homoskedastic residuals. Results are then compared to a second model that assumes heteroskedastic residuals. The test rejected the null hypothesis that there was no heteroskedasticity in the residuals $\left(P > \chi^2 = 0\right)$. For more details on this test, view the STATA documentation [70]. When studying the change in scale variance across many cross-sectional datasets it is not uncommon to find heteroskedasticity [71]. This is not surprising considering the increasing variance of internal temperature as shown in Figure 4. As with serial correlation, once heteroskedasticity is shown to be present, it is relatively straightforward to implement appropriate statistical techniques capable of overcoming these issues.

6.4 Choice of estimators

The tests narrow the scope of possible statistical analyses that are now possible. Heteroskedasticity, intragroup correlations and serial correlations all adversely affect parameter estimates and standard errors. Given the variables in the dataset have both heteroskedasticity and serial correlation it is important to use the correct estimators with correct assumptions. We will therefore estimate the model using several estimation techniques and compare the performance of these estimators. The three estimators chosen for this analysis were GLS, PCSE and XTSCC. All estimators are invoked using STATA11.

7 Results

Results were compared using five different models. The five different models are (1) GLS with heteroskedastic errors only; (2) GLS with heteroskedastic errors and serial correlation; (3) XTPCSE with default assumptions; (4) XTPCSE with default assumptions absent of panel serial correlation; (5) XTSCC with the assumption that the error structure is heteroskedastic and auto correlated up to some lag as well as being correlated between panels. The results of these estimations are presented in Table 5. Further details on each of these estimation techniques can be found in STATA11 documentation [68].

Table 5: Comparison of different estimation methods

Number Obs: **42,723** Groups: **233** Time periods: **184**	**Models**				
	1	**2**	**3**	**4**	**5**
Model Assumptions					
Type of estimator	GLS	GLS	PCSE/OLS	PCSE/OLS	XTSCC
Heteroskedastic errors	yes	yes	yes	yes	yes
Contemporaneous correlation	no	no	yes	no	yes
Serial correlation	no	yes	yes	no	yes
Model Variables					
Text	0.034 (5.41)***	0.09 (21.52)***	0.052 (2.26)*	0.107 (6.34)***	0.052 (2.23)*
Text^2	0.013 (40.51)***	0.005 (23.64)***	0.012 (10.75)***	0.005 (5.67)***	0.012 (7.97)***
(A) London	- -	- -	- -	- -	- -
(A) North East	-1.303 (-30.20)***	-1.525 (-11.18)***	-1.392 (-25.06)***	-1.43 (-8.48)***	-1.392 (-11.34)***
(A) Yorkshire	-0.637 (-15.31)***	-0.989 (-7.53)***	-0.629 (-9.38)***	-0.966 (-6.09)***	-0.629 (-4.50)***
(A) North West	-0.916 (-24.38)***	-1.072 (-9.12)***	-1.031 (-20.57)***	-0.945 (-5.88)***	-1.031 (-11.98)***
(A) East Midlands	-0.501 (-11.62)***	-0.847 (-6.37)***	-0.458 (-10.53)***	-0.779 (-4.93)***	-0.458 (-6.09)***
(A) West Midlands	-0.597 (-15.76)***	-0.927 (-7.74)***	-0.828 (-13.17)***	-0.926 (-6.05)***	-0.828 (-6.69)***
(A) South West	-0.569 (-15.99)***	-0.757 (-6.68)***	-0.765 (-16.40)***	-0.729 (-5.35)***	-0.765 (-8.74)***
(A) East of England	-0.730 (-19.09)***	-0.852 (-6.92)***	-0.667 (-18.52)***	-0.681 (-4.50)***	-0.667 (-10.70)***
(A) South East	-1.332 (-34.18)***	-1.352 (-10.47)***	-1.464 (-35.00)***	-1.361 (-9.82)***	-1.464 (-18.44)***
T_Stat	-0.277 (-12.83)***	-0.338 (-5.20)***	-0.236 (-15.05)***	-0.319 (-4.42)***	-0.236 (-8.73)***
T_SettingResp	-0.078 (-7.38)***	-0.095 (-2.81)**	0.035 (4.18)***	-0.077 (-2.33)*	0.035 (2.02)*
TRV	-0.091 (-3.62)***	-0.077 (-0.96)	-0.169 (-7.76)***	-0.225 (-2.39)*	-0.169 (-4.40)***
CH_Hours	0.055 (34.70)***	0.055 (10.87)***	0.069 (25.96)***	0.055 (9.38)***	0.069 (11.79)***
Reg_Pat	0.882 (19.90)***	0.602 (3.76)***	1.189 (23.72)***	0.683 (4.19)***	1.189 (11.14)***
Auto_Timer	-0.079 (-4.53)***	-0.097 (-1.76)	-0.031 (-2.53)*	-0.069 (-1.34)	-0.031 (-1.27)
HH_Size	0.200 (16.72)***	0.213 (5.21)***	0.25 (20.07)***	0.217 (5.65)***	0.25 (9.19)***
HH_Income	0.125 (18.44)***	0.126 (5.58)***	0.084 (8.73)***	0.118 (5.06)***	0.084 (4.05)***
Child<5	0.752 (23.17)***	0.829 (8.84)***	0.495 (19.67)***	0.765 (7.76)***	0.495 (10.32)***
Children<18	0.157 (9.55)***	0.051 (-0.95)	0.219 (26.48)***	0.029 (-0.59)	0.219 (9.12)***
(B) Age<60	- -	- -	- -	- -	- -
(B) Age60-64	0.148 (6.47)***	0.066 (-0.85)	0.051 (2.19)*	-0.033 (-0.45)	0.051 (-1.04)
(B) Age64-74	0.486 (20.49)***	0.406 (5.31)***	0.37 (14.65)***	0.409 (4.49)***	0.37 (7.45)***
(B) Age>74	0.660 (23.18)***	0.775 (7.62)***	0.585 (22.03)***	0.829 (7.27)***	0.585 (11.12)***
(C) Owner	- -	- -	- -	- -	- -
(C) Renter	0.757 (21.16)***	0.811 (7.09)***	0.94 (32.59)***	0.895 (7.73)***	0.94 (14.75)***
(C) Council	1.263 (41.03)***	1.288 (13.40)***	1.374 (35.27)***	1.303 (14.18)***	1.374 (17.90)***
(C) H_Assoc	0.667 (15.87)***	0.873 (6.09)***	0.448 (15.10)***	0.867 (6.90)***	0.448 (8.27)***
WE_Same	-0.572 (-22.78)***	-0.515 (-6.24)***	-0.438 (-26.95)***	-0.56 (-6.79)***	-0.438 (-12.85)***
WE_Temp	0.049 (3.20)**	0.083 (13.64)***	-0.038 (-0.59)	0.088 (2.82)**	0.038 (-0.68)
(D) Detached	- -	- -	- -	- -	- -
(D) SemiDet	0.740 (34.13)***	0.623 (8.93)***	0.694 (29.90)***	0.683 (8.98)***	0.694 (13.38)***
(D) Terraced	0.664 (27.67)***	0.671 (8.54)***	0.607 (33.31)***	0.69 (9.61)***	0.607 (17.36)***
(D) NotHouse	0.621 (18.44)***	0.428 (4.07)***	0.541 (21.42)***	0.327 (3.28)**	0.541 (11.93)***
Gas_CH	-0.691 (-19.57)***	-0.566 (-5.03)***	-0.564 (-24.93)***	-0.57 (-4.71)***	-0.564 (-11.88)***
Non_CH	0.179 (6.58)***	0.071 (-0.78)	0.058 (4.60)***	-0.054 (-0.63)	0.058 (2.33)*
Elec_Main	0.140 -1.95	-0.103 (-0.42)	1.008 (13.20)***	-0.07 (-0.29)	1.008 (6.46)***
Gas_OH	-0.094 (-3.45)***	0.007 (-0.07)	-0.071 (-4.77)***	-0.007 (-0.08)	-0.071 (-2.17)*
Elec_OH	0.081 (2.60)**	0.245 (2.51)*	-0.195 (-8.14)***	0.285 (3.09)**	-0.195 (-4.32)***
Other_OH	-1.091 (-32.00)***	-0.951 (-8.36)***	-1.016 (-32.29)***	-0.88 (-7.55)***	-1.016 (-17.69)***
Build_Age	0.054 (12.59)***	0.058 (4.16)***	0.042 (8.07)***	0.039 (2.59)**	0.042 (4.12)***
Roof_Ins	0.081 (18.85)***	0.07 (5.10)***	0.125 (32.72)***	0.07 (4.88)***	0.125 (15.06)***
Dbl_Glz	0.190 (27.31)***	0.206 (9.17)***	0.188 (25.44)***	0.225 (10.39)***	0.188 (12.44)***
Wall_U	0.072 (8.48)***	0.067 (2.88)**	0.076 (9.18)***	0.086 (3.69)***	0.076 (4.54)***

Alpha (constant)	15.080 (170.88)***	15.819 (58.35)***	14.224 (79.91)***	15.599 (44.58)***	14.224 (46.27)***
Summary Statistics					
χ^2	51,201***	14,292***	50,398***	3,250***	-
Log Likelihood	-77,840	-	-	-	-
RMSE	1.87	1.95	1.84	1.93	1.84
R^2	-	-	0.45	0.88	0.45

* p<0.05, ** p<0.01, *** p<0.001, t-statistics are in parenthesis

It is worth noting that several other estimation techniques were also tested but not included in the table above. The PCSE estimator was tested with and without the assumption of heteroskedastic errors and within panel serial correlation. These produced very similar estimates as shown in Model (4), with differences in standard errors. The GLS estimator was also tested with the assumption that standard errors were IID and had no within panel serial correlation. These parameter estimates were the same as in Model (1), with differences in standard errors. The robust estimator was tested and provides estimates that are robust to autocorrelation and heteroskedasticity. It calculates the parameter estimates and standard errors using a linearised variance estimator instead of finding the minimum sum of squared errors. Results from robust regression produced the same parameter estimates as both PCSE and XTSCC with differences in the structure of standard errors.

Due to the way these different estimation methods work they do not all report similar summary statistics. This makes it difficult to compare these models against each other. For example, when estimating a model using generalised least squares (GLS) estimation it is not possible to calculate an R^2 statistic. Similarly, it is not straightforward to calculate the log-likelihood when OLS estimation is used. One summary statistic that is calculable by all estimation techniques is the root mean square error (RMSE). The root mean square error can be calculated using Equation (1.8). It represents the squared sum of differences between actual measurements, y, and predicted measurements, $\hat{y}$. The sum of squared differences is then divided by the number of degrees of freedom in the model, where N is the total number of observations and k is the number of covariates used to estimate the model – thus it rewards parsimony. The smaller the RMSE value the better the model is able to predict the actual values.

$$RMSE = \sqrt{\frac{\sum(y-\hat{y})^2}{(N-k-1)}} \tag{1.8}$$

When reviewing Table 5 it becomes immediately clear that almost all parameters are statistically significant in at least one of the five models tested. This highlights the importance of using the correct estimation technique with good understanding of the assumptions that are being used for the distribution of standard errors. Given the difficulty in assessing the different models, Figure 5 was produced to compare how different estimation methods are able to predict mean internal temperatures. The graph on the top of Figure 5 contains a scatter plot of all mean daily internal temperatures and the line graphs represents the recorded mean internal daily temperature alongside the five different models used to predict mean internal temperature. Due to the long time scale used for this model, it is difficult to differentiate the predictability of the different models on a single line plot. Therefore three additional line plots that use shorter time periods (as indicated by the shaded areas) are shown below this line graph.

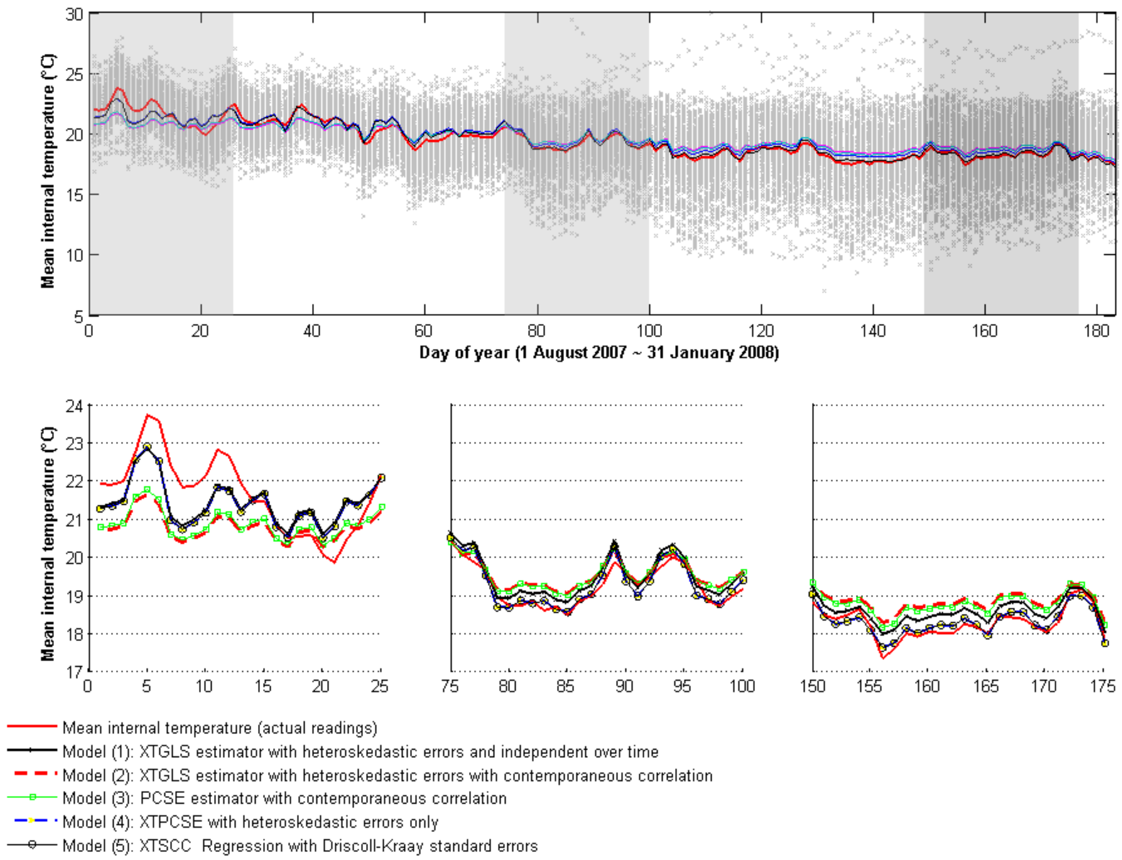

Figure 5: Comparison of different estimation techniques

Reviewing the three lower graphs of Figure 5 it is clear that the accuracy of model predictions vary over time. Studying the graph on the lower left, Model (1), Model (4) and Model (5) give the closest predictions for mean internal temperature and essentially overlay each other on the same path. For the winter period, represented by the line graph on the lower right of Figure 5, Model (1) appears to have broken away from the original set leaving Model(4) and Model(5) to be the best estimators of mean internal temperature.

Another way to check how well the model is predicting actual measurements is to compare the distributions of the predicted values with the distributions of the recorded values. Table 6 gives these statistics for each of the different models. The distributions of all predictive models match fairly closely to the distribution of actual values. However, all modelled distributions predict under dispersion and have difficulty in matching minimum and maximum temperatures. This is not considered to be a significant problem as temperatures in the tail-ends of distributions happen rarely, with very low temperatures most likely due to dwelling vacancy.

Table 6: Comparison of the distributions of predicted with actual temperature readings

Model	Variable	$\overline{x}$	Median	σ	Min	Max
Actual readings	y_{Tin}	19.46	19.64	2.47	7.05	29.92
Model (1)	$\hat{y}_1$	19.60	19.46	1.64	14.74	26.44
Model (2)	$\hat{y}_2$	19.62	19.58	1.32	15.17	24.57
Model (3)	$\hat{y}_3$	19.51	19.36	1.72	14.39	27.06
Model (4)	$\hat{y}_4$	19.61	19.57	1.37	14.81	24.80
Model (5)	$\hat{y}_5$	19.51	19.37	1.72	14.40	27.04

Given the evidence presented above, Model (5) (XTSCC) was chosen as the best model for predicting internal temperatures. Key statistics for this model are given in Table 7.

Table 7: Key statistics for final panel Model (5)

Number Obs: **38,501** Groups: **210** Time periods: **183** Method: **Pooled OLS** Maximum Lag: **4**	β	B	Driscoll Kraay Std. Errors	t-stats	95% confidence intervals	
Text	0.052	0.096	0.023	(2.23)*	0.006	0.098
Text^2	0.012	0.455	0.002	(7.97)***	0.009	0.016
(A) London		-				
(A) North East	-1.392	-0.135	0.123	(-11.34)***	-1.634	-1.150
(A) Yorkshire	-0.629	-0.07	0.140	(-4.50)***	-0.904	-0.353
(A) North West	-1.031	-0.153	0.086	(-11.98)***	-1.201	-0.862
(A) East Midlands	-0.458	-0.049	0.075	(-6.09)***	-0.606	-0.309
(A) West Midlands	-0.828	-0.123	0.124	(-6.69)***	-1.072	-0.584
(A) South West	-0.765	-0.112	0.088	(-8.74)***	-0.938	-0.593
(A) East of England	-0.667	-0.089	0.062	(-10.70)***	-0.790	-0.544
(A) South East	-1.464	-0.172	0.079	(-18.44)***	-1.620	-1.307
T_Stat	-0.236	-0.047	0.027	(-8.73)***	-0.289	-0.183
T_SettingResp	0.035	0.011	0.017	(2.02)*	0.001	0.069
TRV	-0.169	-0.028	0.038	(-4.40)***	-0.244	-0.093
CH_Hours	0.069	0.143	0.006	(11.79)***	0.058	0.081
Reg_Pat	1.189	0.158	0.107	(11.14)***	0.978	1.399
Auto_Timer	-0.031	-0.006	0.025	(-1.27)	-0.080	0.018
HH_Size	0.250	0.114	0.027	(9.19)***	0.196	0.304
HH_Income	0.084	0.049	0.021	(4.05)***	0.043	0.124
Child<5	0.495	0.053	0.048	(10.32)***	0.401	0.590
Children<18	0.219	0.068	0.024	(9.12)***	0.171	0.266
(B) Age<60		-				
(B) Age60-64	0.051	0.007	0.049	(-1.04)	-0.046	0.148
(B) Age64-74	0.370	0.058	0.050	(7.45)***	0.272	0.468
(B) Age>74	0.585	0.083	0.053	(11.12)***	0.481	0.688
(C) Owner		-				
(C) Renter	0.940	0.088	0.064	(14.75)***	0.814	1.066
(C) Council	1.374	0.151	0.077	(17.90)***	1.222	1.525
(C) H_Assoc	0.448	0.038	0.054	(8.27)***	0.341	0.555
WE_Same	-0.438	-0.074	0.034	(-12.85)***	-0.505	-0.370
WE_Temp	0.038	0.007	0.056	(-0.68)	-0.072	0.149
(D) Detached		-				
(D) SemiDet	0.694	0.125	0.052	(13.38)***	0.591	0.796
(D) Terraced	0.607	0.103	0.035	(17.36)***	0.538	0.676

(D) NotHouse	0.541	0.075	0.045	(11.93)***	0.452	0.630
Gas_CH	-0.564	-0.083	0.047	(-11.88)***	-0.657	-0.470
Non_CH	0.058	0.011	0.025	(2.33)*	0.009	0.108
Elec_Main	1.008	0.108	0.156	(6.46)***	0.700	1.315
Gas_OH	-0.071	-0.014	0.033	(-2.17)*	-0.135	-0.006
Elec_OH	-0.195	-0.027	0.045	(-4.32)***	-0.284	-0.106
Other_OH	-1.016	-0.134	0.057	(-17.69)***	-1.129	-0.902
Build_Age	0.042	0.036	0.010	(4.12)***	0.022	0.062
Roof_Ins	0.125	0.106	0.008	(15.06)***	0.109	0.142
Dbl_Glz	0.188	0.102	0.015	(12.44)***	0.158	0.217
Wall_U	0.076	0.029	0.017	(4.54)***	0.043	0.108
Alpha (constant)	14.224	-	0.307	(48.53)***	13.618	14.830
R^2	0.45	*RMSE*	1.84	*Prob > F*		0

* p<0.05, ** p<0.01, *** p<0.001, t-statistics are in parenthesis

Each of the parameter coefficients, β, are subject to the same units as the underlying covariate. For example the β value for *Text* is measured in °C, implying that a 1°C change in external temperature will result in a change of ~0.064°C to the internal temperature (0.052°C+0.012°C). As different covariates are measured by different units, the magnitude of different coefficients cannot be used to compare the overall importance of different factors as they relate to internal temperature. In Table 7, we therefore also include a standardised parameter coefficient, B , making it possible to compare the importance of all the covariates in the model. The higher the B value, the more influence or effect that variable has on internal temperature. After standardisation, all covariates are comparable against the response variable. The B -value therefore simply represents the number of standard deviations change from the mean that will occur in the response variable from one standard deviation change (positive or negative) in the predictor variable. In sum, the standardised coefficients can thus be used to compare the relative importance of different variables as they influence internal temperature.

Benefiting this study is that many of the variables used in the analysis are dummy variables. Because all dummy variables have the same upper and lower bounds (and unit of measure), it is possible to compare parameter estimates from the coefficients of the dummy variables. Moreover, because dummy variables are a unit response they directly indicate the predicted change in degrees Celsius on the response variable. Any dummy variable that does not belong to a multicategory group represents the direct change this variable will have on internal temperature. For example if a child under five is present in the dwelling then the mean internal daily temperature is expected be ~0.5°C warmer when compared to a home without a child, ceteris paribus.

For dummy variables belonging to a multi-category group, the parameter coefficients represent the change to internal temperature with respect to that comparison category. For example, the regional β coefficients are all negative indicating that the mean internal temperature for London dwellings is higher than all other regions. This is due to a combination of factors, but most likely caused by high density housing and smaller living spaces making homes in London easier to heat and thus leading to higher internal temperatures. The result may also suggest the presence of a heat island effect. Due to the complexity of this phenomenon more conclusive analysis is needed, and certainly beyond the scope of this study.

7.1 Model Diagnostics

Post panel regression diagnostics were completed on all models. Residual plots remain the best check against violation of standard regression assumptions. The creation of several different residual plots confirmed that key model assumptions were upheld. Multicollinearity between model variables was tested post estimation using Variance Inflation Factors (VIFs). VIF is a measure of how much the variance of an estimated coefficient increases if the explanatory variables are correlated. The higher the VIF, the greater the degree of collinearity. Values greater than 10 suggest substantial collinearity amongst predictors and may lead to inflated parameter coefficients [72]. The explanatory variables used in this model had a combined VIF of 2.71 suggesting there is no problem with multicollinearity. Residual plots and histograms showed that errors were centred about the mean with properties closely matching a normal distribution.

7.2 Robustness and validation checks

The benefit of using a large random sample is that it allows a sub-sample to be withheld prior to estimation for use in post estimation and cross-validation. Before any model estimation was completed, a random sample consisting of 10% of the original sample was withheld (27 observations). If, on the other hand, the complete dataset was used to estimate the model, self-influence from data remaining in the model would distort the accuracy of post validation tests. Said differently, all data-points included in the estimation of the model pull the estimation parameters closer to these values. Therefore removing a subsample prior to estimation and using this for validation purposes offers a robust check of model accuracy. Figure 6 shows the predicted versus actual temperature readings for dwellings that were withheld from the estimation procedure. As shown, the predictability of the model remains strong and follows the peaks and troughs of the recorded internal temperature readings relatively well. Given the volatility of recordings, the model is particularly effective at predicting mean internal temperature.

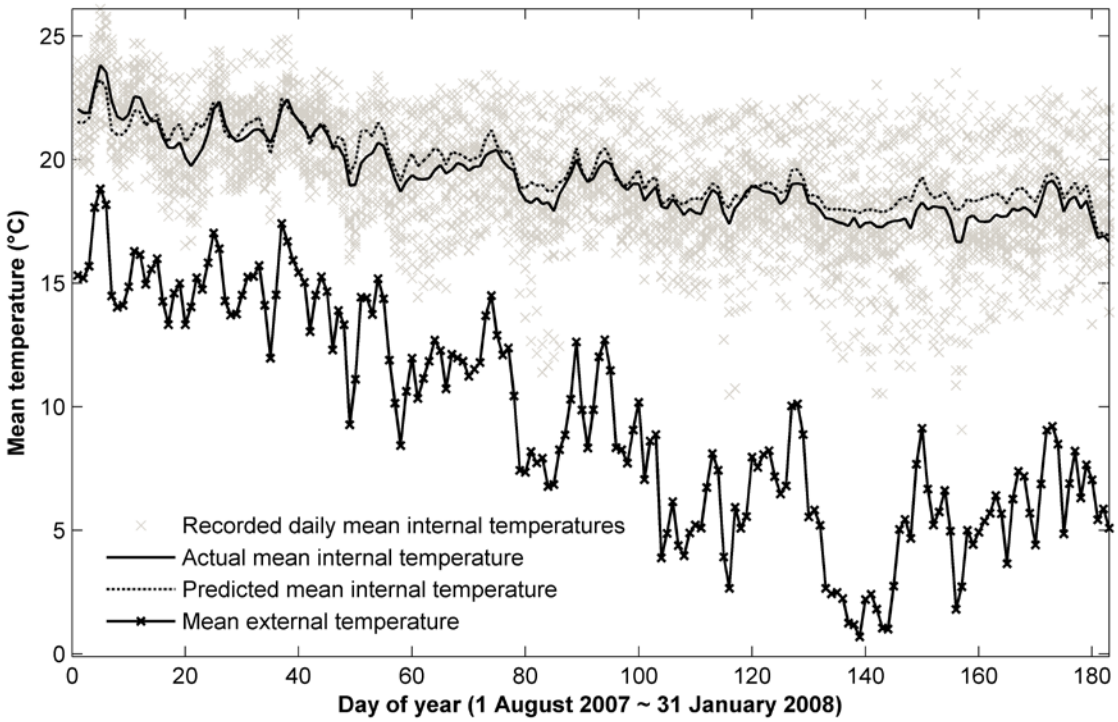

Figure 6: Validation sample compared with actual mean internal temperature

Figure 7 shows a plot of predicted versus actual temperature readings for one of the dwellings belonging to the subsample withheld from the original estimation. Once again, the close prediction between predicted and actual internal temperatures remains strong. The temperature profile of this particular dwelling was chosen because it shows two distinct periods where temperatures have dropped markedly due to insufficient heating. The cause of this is most likely due to the building being unoccupied over a weekend. The graph shows two periods of inactive heating that were not predicted by the model.

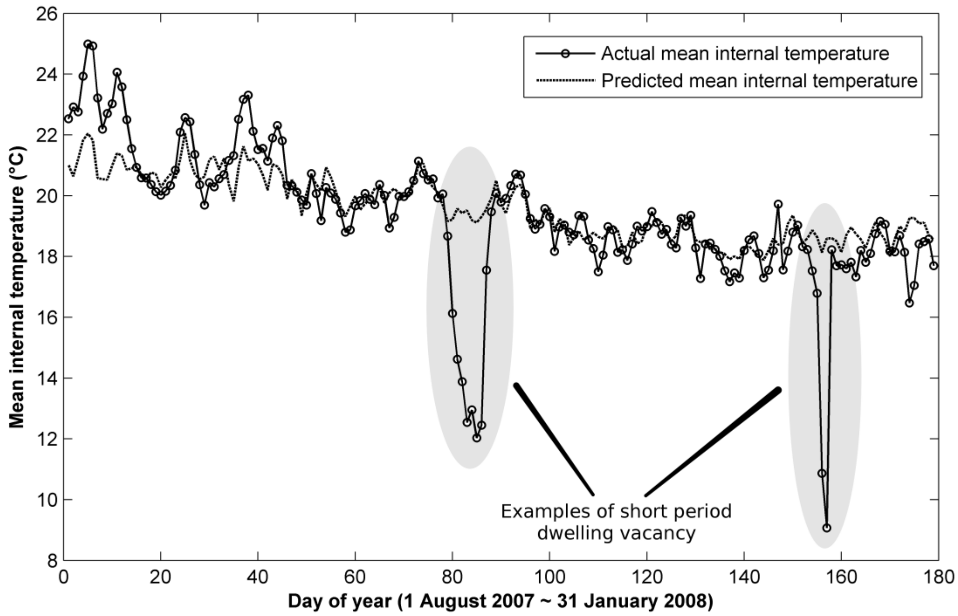

Figure 7: Predicted and actual internal daily temperature measurements for one dwelling

The model diagnostics presented thus far show the model performs well and is thus relatively accurate at making predictions. An important next step is to show the width of precision of model estimates (i.e. the width of the 95% confidence intervals). There are two choices for forming confidence intervals around $\hat{y}$:

i) predict a single observation that is yet to be observed and the range of values that this will most likely fall between (prediction interval);

ii) predict the average value for the entire building stock and predict the range of values this will most likely fall between (confidence interval).

The bands around the prediction interval are generally much wider than the bands around the confidence interval. This is because confidence intervals average out extreme values, and therefore only requires that the average value is within the specified confidence interval. It is possible to calculate the standard error of the prediction interval (in percent) using Equation (1.9) [73].

$$S.E = 100\sqrt{\frac{\sum\left(\frac{y-\hat{y}}{y}\right)^2}{N-2}} \qquad (1.9)$$

Using this formula we can conclude that a future prediction for a single dwelling will deviate from the actual value by an average of 11.14%. Alternatively, standard errors can be calculated and used to represent prediction intervals. Using a 95% confidence prediction interval, the predicted value for a random dwelling will be within ±3.66°C of the recorded temperature for that day. Alternatively, we can show the confidence interval for the mean of internal temperature across all dwellings deviates by an average of 1.74%. Thus we can be 95% confident that the predicted mean internal temperature across all dwellings is within ±0.71°C of the actual mean internal temperature for the entire building stock.

8 Discussion

The model developed and described above is the first time internal temperature has been predicted for a national building stock using panel-methods. The benefit of this statistical method is that it allows us to retain valuable information about temperature as it varies over time and across a heterogeneous building stock. It also allows us to combine a large number of different variables that are known to individually affect internal temperature. Variables were chosen to represent the physical properties of the building, the external climate, behavioural and socio-demographic properties of occupants as well as the dwelling's geographic location. The model is able to predict daily mean building stock internal temperature to within ±0.71°C at 95% confidence.

Statistical inferences drawn from the magnitude of variables offer insight into what factors are important for explaining internal temperature demand. As shown in Table 5 most of the variables included in the model are highly statistically significant. Many of the variables also have a large magnitude and explain between 0.01 to 0.5 standard deviations of daily internal temperatures. Moreover, the model is able to explain 45% of the variance (R^2 = 0.45) of internal temperature demand from dwellings belonging to the English residential sector.

8.1 Intransmutable variable effect

Intransmutable variables are variables that cannot be manipulated to have an effect on internal temperature. Examples include the external temperature and the geographic location of the dwelling. External temperatures are shown to be an important factor explaining the fluctuations of daily internal temperature. Moreover, it is shown that these effects are non-linear with higher external temperatures explaining a greater proportion of the variance of internal temperatures. Geographic location was included to control for any remaining unobserved heterogeneity between dwellings. London was shown to have higher mean internal temperatures than any other location in England. This is most likely due to high-density housing (e.g. smaller dwellings are easier to heat). The regions having the lowest mean internal temperatures were the North East and South East. The combined effect of all intransmutable variables explain between ~0°C and ~6.8°C of the variance amongst dwellings for minimum and maximum external temperatures.

8.2 Heating control effect

Using the model it is possible to make inferences about the effect of different forms of heating controls. The effects of thermostat settings and heating controls has most thoroughly been looked at by Shipworth [2,22]. In order to compare this research with earlier studies, five different forms of user control over internal temperature were analysed; these were:

i) the presence of a thermostat;

ii) the set point temperature of the thermostat;

iii) whether the only type of heating control in a dwelling is with a thermostatic radiator valve; and,

iv) the use of an automatic timer as opposed to control of the heating system by manual operation.

The results suggest that the mere presence of a thermostat has the effect of reducing average internal temperature by ~0.24°C on average. When thermostatic radiator valves are the only type of heating control, they again reduce internal temperature by an average of ~0.17°C, compared to homes without any control at all. This result contrasts with Shipworth et al. [22] where they found no statistically significant difference in temperatures between homes with and without room thermostats. There are several important reasons for this discrepancy, even though the dataset used in both analyses were the same, but the periods analysed were different[9]. In the analysis completed by Shipworth et al. [22] maximum daily temperatures were averaged over the entire survey period to give a single maximum average daily temperature for each dwelling (i.e. a cross sectional study). In this analysis the arithmetic mean daily temperature is used and it is not averaged over time thus giving a panel dataset. The benefit of using panel methods is that the heterogeneity in daily temperature fluctuations is retained. Furthermore, maximum daily temperatures only capture the highest recorded temperature in a day; mean daily temperatures on the other hand capture the average of internal temperatures recorded over the whole day, thus giving a better picture of the relative heating profile of a dwelling. In Shipworth et al. an analysis of variance (ANOVA) is performed to determine the correlation between maximum internal temperature and the presence of a thermostat without controlling for other substantive factors. In this analysis, a large number of covariates known to affect internal temperature (like external temperature) are controlled for, and therefore a more accurate picture of the 'real' effect that thermostats may have on internal temperatures is therefore achieved.

The respondent specified thermostat set-point has the effect of increasing internal temperatures, as is expected (e.g. higher thermostat set-points lead to higher internal temperatures). In this model, each household's thermostat setting was grouped into four

[9] Shipworth et al. [22] used a three month period from 1st November 2007 – 31st January 2008.

discrete categories [<18, 18-20, 20-22, >22]. The analysis shows that each time a household increases its thermostat set-point category the mean daily internal temperature of the dwelling will increase by ~0.035°C. This implies that on average, the variation in temperature difference between a dwelling with a set-point temperature below 18°C and a dwelling with a set-point temperature above 22°C will be ~0.14°C, ceteris paribus. This shows that thermostat settings have an important role to play in reducing overall household energy consumption. Although this conclusion supports earlier research completed by Shipworth [22] we recommend more detailed analysis looking specifically at the effect of thermostat set-points and internal temperatures on energy demand over time.

Interestingly, the use of an automatic timer does not lead to a statistically significant change to internal temperature when compared with a heating system that is controlled manually. In a similar analysis completed by Shipworth et al. [22] it was found that the presence of an automatic timer has no statistically significant effect on the length of heating duration[10]. These results are most likely due to the way timers are used by occupants. Manual systems require occupants to interact with their heating system and request heating when required – this requires mental and physical effort from the occupant introducing a natural threshold or level of discomfort that must first be overcome before the occupant can be bothered to alter their heating system. The corollary to this is also true. Central heating systems maybe switched on and then remain on long after heating is required. Automatic timers on the other hand are programmed to start and stop heating at predetermined periods. Some occupants may set their timers at the beginning of winter and leave them on for the duration of the heating season, regardless of occupancy or external conditions. An early winter cold snap may precipitate the automatic timer being set early and therefore extend the length of the heating season. Furthermore, automatic timers do not require additional user interaction, and will automatically switch on whether heating is required by the occupant or not. This result suggests that it is not the presence of the automatic timer *per se*, but how people choose to interact with the technology that really matters. The final result implies that on average there is no statistical difference in internal temperatures for homes that use an automatic timer compared to homes that control heating manually. The combined effect of all forms of heating control are able to explain up to ~0.38°C of the variance in mean internal temperatures across dwellings.

8.3 Human behaviour effects

In addition to the use of heating controls, behavioural variations across the building stock were captured using variables to measure the duration of heating periods and the regularity of heating patterns. Both variables were recorded from the occupants' responses to survey questions. This analysis shows that for each additional hour of heating duration, mean daily

[10] In Shipworth et al [22] the heating duration was estimated as the period of time when internal temperatures within a dwelling are increasing.

internal temperature increases by ~0.07°C. Thus a home that has its heating on for one hour per day, compared with home that has its heating on for four hours per day will have a difference in mean daily internal temperature of ~0.28°C. If a respondent answered positively to having a regular heating pattern, the mean internal temperature would also be ~1.19°C higher than a home without a regular heating pattern. This implies that occupant's with routine energy habits, consume more energy than those who do not have such routines. This result presents strong quantitative evidence in support of more qualitative studies completed in the fields of psychology [74] and sociology [75] where it is believed that social norms and habitual behaviours are important for understanding energy consumption (see Triandis' Theory). This analysis goes one step further and shows that households who have routine energy behaviour may actually have increased energy consumption compared to households who do not have a fixed routine.

The effect of weekends on internal temperature is also worth consideration. When a dwelling is occupied, we would expect weekend temperatures to be higher than average as people are generally more likely to be at home. However, the final effect of weekends on internal temperature is shown to be statistically insignificant. As previously discussed, the model is not able to predict when a dwelling is unoccupied and in such circumstances will lead to lower temperatures (assuming heating is switched off). The statistically insignificant result is most likely due to these two confounding effects. A second survey question asked if heating patterns over the weekend were typically the same as heating patterns during the week. If the response was positive, this had a statistically significant negative effect, reducing internal temperature by an average of -0.44°C, *ceteris paribus*. This implies households who responded they had different heating patterns on the weekend, tend to heat their homes for longer and/or to higher temperatures. The corollary of this is that households with the same heating pattern all week (weekday and weekend) will have lower than average internal temperature on the weekend. In sum, the combined effect of heating duration and regularity of heating patterns may explain up to ~2.87°C of the variation in internal temperatures across all dwellings.

8.4 Socio-demographic and occupancy effects

Kelly [31] showed that the number of people living in a dwelling represents one of the most important determinants for explaining dwelling energy consumption. The results presented in this analysis support this finding. For each additional person living in a dwelling the mean daily internal temperature increases ~0.25°C on average. Thus a dwelling with a family of five would be ~1.25°C warmer than a single person household. Kelly [31] also showed that income has both a direct and indirect effect on final energy consumption. For this analysis net household income was separated into seven discrete income bands with the lowest band representing household incomes less than £5,199 and the highest band representing income greater than £95,000. The median income was ~£24,000/annum. For each jump in income bracket, the mean household temperature increases by ~0.085°C. Therefore the mean difference in temperature between a household in the lowest income bracket compared to a household in the highest income bracket is approximately ~0.59°C.

The age of different occupants is a significant driver of internal temperatures. The presence of a child under five years old increases the mean internal temperature by an average of ~0.5°C compared to a home where no child is present. The number of children under 18 also increases the internal temperature by ~0.22°C for each additional child. It is no surprise that dwellings with older occupants have higher internal temperatures. The internal temperature for a dwelling where the oldest person is aged 60-64 is not statistically different from a dwelling where the oldest person is under 60. However, a home where the oldest person is aged 64-74 will be ~0.37°C warmer than home where everyone is under 60. And a home where the oldest person is over 74 will be ~0.59°C warmer. For households with occupants over retirement age there is a clear statistically significant trend for increasing mean internal temperature. This clearly shows that older people have their heating on for longer and require higher temperatures. In total, ~3.69°C of the variance in internal temperatures can be explained by socio-demographic factors alone.

8.5 Tenure effect

Four categories were chosen to model the effects of different tenure types on temperature. Owner-occupiers were chosen as the comparison category. Each of the three other categories (privately rented, council owned and housing association) had higher mean internal temperatures than owner-occupiers. The cause of this seemingly surprising result may have something to do with the employment status of occupants. In England, 91%[11] of owner occupiers with a mortgage are employed. Employment reduces to 67% in the private rented sector, 30% for local authority tenants and 32% for RSL or housing association tenants[12]. Occupants in full-time employment spend less time at home and therefore require less heating, lowering the mean daily internal temperature. Employment status was not controlled for as it was not collected during the survey. Occupants living in a home belonging to a housing association will have mean internal temperatures that are on average ~0.49°C warmer than owner occupiers, while rented dwellings are on average ~0.94°C warmer and council tenants are ~1.37°C warmer. Owner occupiers also live in larger dwellings and larger dwellings are harder to heat. From the EHCS (2008) it can be shown that 29% of owner occupiers live in homes that are larger than 110 m^2; compared to 13% of privately rented dwellings and less than 2.5% for local authority and housing association tenants. Another strong argument supporting the clear differences in temperatures, is the energy efficiency rating (EER) between different tenure types. The 2007 English House Condition Survey shows that 65% of owner occupiers live in a dwelling with a building efficiency grade lower

[11] 55% of owner occupiers in England have a mortgage.
[12] These statistics were calculated from the English House Condition Survey [76].

than “D”. When compared with other tenure types such as privately rented (60%); council owned (39%) and RSL (29%), owner occupiers have the least efficient homes in the housing stock. This is most likely because of government initiated programs supporting improved energy efficiency in social housing. Tenure therefore explains up to a maximum of ~1.37°C of the variance of internal temperature between dwellings.

8.6 Heating system effects

A variety of physical characteristics were chosen to model the efficiency of heating systems and the building envelope. If gas central heating is present in the dwelling this lowers mean internal temperature, decreasing it on average by ~0.56°C when compared to a house without gas central heating. Given that over 90% of dwellings in England have gas central heating, it is difficult to draw any more conclusive insight from this result. Households with other forms of heating systems (which may also include homes with central heating) have a marginal positive effect on internal temperature (~0.06°C), although the statistical significance of this result is not strong compared to the other results *($p<0.05$)*. Homes that use electricity as a primary heat source are on average ~1.0°C warmer than homes using other heat sources. This is most likely due to the effect of electric storage heaters that take advantage of off-peak electricity prices and slowly release heating over a long period maintaining regular internal temperatures.

Many homes have additional heating systems in the main room of the house. The effect of additional heating systems on internal temperature was also studied. All fuel types used in additional heating systems (gas, electricity, other) have a negative effect and therefore reduce mean internal temperatures. Gas and electric main room heaters decrease internal temperatures by ~0.07°C and ~0.2°C respectively. The largest effect however comes from main room heaters fuelled by alternative fuels such as wood, coal or oil. The overall effect from these heaters reduces mean internal temperatures in the home by approximately ~1.0°C. The effect of main room heaters on internal temperature is therefore important. This finding suggests homes with living room heaters provide occupants with the opportunity to use different heating sources and thus the ability to heat only the main room of the house, reducing the need for a central heating system that would otherwise heat the whole house. The combined effect of different heating systems may explain up to ~2.0°C of the variance of mean internal temperatures.

8.7 Building efficiency effects

Several variables were identified to control for the effects of building efficiency on internal temperature. The variable representing roof insulation contains eight categories, with each category roughly increasing insulation by 25mm (see Table 4) and improving internal temperature by an average of ~0.13°C. Therefore, the temperature difference between a home with no roof insulation and a home with greater than 200mm of roof insulation is approximately ~1.0°C on average. The efficiency of walls as indicated by its U-Value, also increase internal temperature. The average U-Value for the exterior walls of each dwelling were categorised into four discrete bins [<0.4, 0.4-0.6, 0.6-1.6, >1.6]. For each improvement in the U-value category, the internal temperature increased by an average of ~0.08°C. Thus the difference in temperature between the best and worst performing categories explains ~0.32°C of the variation. The extent of double glazing also contributes markedly to internal temperature. For each dwelling the extent of double glazing was separated into five discrete bins [None, < ½, ~½, >½, All]. Improving the proportion of double glazing in a dwelling by one category has the effect of increasing the mean internal temperature of that dwelling by an average of ~0.19°C. A dwelling that goes from having no double glazing to having full double glazing will increase the internal temperature by an average of ~0.94°C.

Building typology explains up to ~0.7°C of the variance of internal temperature between different dwellings. As expected, detached homes have the lowest internal temperature and are ~0.7°C colder than semi-detached dwellings; ~0.61°C colder than terraced dwellings and ~0.54°C colder than homes not considered a house (e.g flats and apartments). The age of the dwelling was modelled using ten discrete categories ranging in construction period from prior to 1900 to post 2003. For each category improvement in the age of construction the mean internal temperature increases by ~0.04°C on average. Therefore, a building constructed after 2003 when compared to a building constructed prior to the 1900's will on average be ~0.42°C warmer, *ceteris paribus*. When all physical building effects are combined, it is possible to explain up to ~3.38°C of the variance of internal temperatures amongst heterogeneous dwellings.

8.8 Quantifying the rebound effect

These results are consistent with both theory and previous empirical research. However, because these different effects are quantified this research has important implications for policy-makers. In particular this research may prove instrumental in helping understand and quantify the rebound effect. It is now increasingly common for government policy to allow a percentage of the anticipated energy savings to be lost due to the take-back[13] effect (usually estimated about 20% [77,78]). This effect is not well understood and usually arbitrarily applied consistently across all dwellings. This research provides researchers and policy makers with a simple tool to estimate the likely increase to internal temperature that will occur due to energy efficiency improvements on a discrete dwelling with a known set of socio-demographic, behavioural and physical parameters. Armed with improved understanding for how internal temperature may be affected by energy efficiency improvements, it is therefore possible to quantify the rebound effect. As this analysis allows for a diverse building stock with a wide range of different socio-demographic attributes, it is

[13] Take-back is also known as the direct rebound effect.

possible to model the effects that different policies will have on internal temperature and therefore quantify the amount of rebound expected for different dwellings.

9 Conclusion

We present a panel model for predicting and making inferences about the diversity of mean daily internal temperatures across the English domestic building stock. The model explains 45% of the variance of internal temperature and can predict the daily mean building stock internal temperature to within ±0.71°C of actual recorded temperature with 95% confidence. Daily fluctuations in external temperature are shown to impact internal temperatures non-linearly and to the second power. We show the mere presence of heating controls such as thermostats and thermostatic radiator valves lowers mean internal temperatures; however, the use of automatic timers is not statistically significant. As expected there is a clear positive relationship between respondent specified thermostat set-point temperature and internal temperature; higher thermostat set-points lead to higher internal temperatures. The respondent specified average number of daily heating hours increases internal temperatures by an average of ~0.07°C for each additional hour of heating.

This research provides quantitative evidence supporting hypothesis from sociology (practice theory) and psychology (habitual behaviour) that routine behaviours are important drivers of home energy consumption. Households who responded with regular weekly heating patterns are on average ~1.19°C warmer than households with an irregular heating pattern. However, households who responded with different heating patterns over the weekend compared to the working week were on average ~0.44°C warmer than homes who responded they kept the same heating pattern for the whole week.

As established by existing empirical research, both household income and household occupancy are important indicators and lead to an increase in mean internal temperature. Households with annual incomes over £95,000 in 2007-08 are ~0.59°C warmer on average than households with annual incomes under £5,199. For each additional occupant, internal temperatures are shown to increase by ~0.25°C. Socio-demographic variables such as the age of occupants are also important drivers of internal temperature demand. The presence of a child under five, is shown to increase internal temperatures by an average of ~0.5°C while each child under the age of 18 increases mean internal temperature by ~0.22°C for each additional child. The presence of an elderly person over the age of 75 increases internal temperature by ~0.56°C more than a home where the oldest person is under 64. On average, owner occupiers live in the coldest homes and council tenants live in the warmest.

Heating systems also affect internal temperatures. Homes that use electricity as their primary heating fuel are on average ~1.0°C warmer than homes that use other fuels. Homes that have secondary heating systems in the living room have lower internal temperatures when compared to homes that do not have secondary heating systems. This implies living room heaters give occupants the opportunity to just heat the main room in the house, therefore lowering the mean temperature in the rest of the house. Building efficiency measures such as cavity wall insulation, loft insulation and double glazing all have the effect of increasing the mean internal temperature of the dwelling.

Looking at the combined effect of different variables, it is possible to gain deeper insight into the most important factors that explain mean internal temperatures. Intransmutable variables (external temperature and geographic location) explain up to ~6.8°C of the variance of internal temperatures when external temperatures are high. Heating controls explain ~0.38°C of variance, behavioural variables explain ~2.87°C and socio-demographic factors explain up to ~3.69°C. Differences in tenure may explain up to ~1.37°C and different heating systems explain ~2.0°C. Capturing the wide range of different building efficiency measures may explain up to ~3.38°C of the variance with double glazing and roof insulation both explaining about ~1.0°C each. In sum, behavioural and socio-demographic factors combined may explain up to ~6.56°C of the variance of internal temperatures and therefore must be appropriately accounted for if energy demand estimations are to be accurate.

In summary, this panel model presents a unique opportunity for future building stock models to incorporate the dynamics of internal temperature demand. Moreover, the model can be adapted to quantify the take-back effect (through estimation of changes to internal temperatures) on discrete dwellings as combinations of different energy efficiency measures are applied. The model can be implemented at any scale and allows modellers to include behavioural and socio-demographic factors to estimate there effect on internal temperature.

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