Do homes that are more energy efficient consume less energy?: A structural equation model for England's residential sector

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May 2011

CWPE 1139 & EPRG 1117

EPRG WORKING PAPER

UNIVERSITY OF CAMBRIDGE

Electricity Policy Research Group

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Keywords residential; energy; modelling; SAP; structural equation efficiency

JEL Classification C50, Q4

EPRG WORKING PAPER

Contact sjk64@cam.ac.uk
Publication May 2011
Financial Support Cambridge Trusts / Cambridge Econometrics / 4CMR

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Energy consumption from the residential sector is a complex socio-technical problem that can be explained using a combination of physical, demographic and behavioural characteristics of a dwelling and its occupants. A structural equation model (SEM) is introduced to calculate the magnitude and significance of explanatory variables on residential energy consumption. The benefit of this approach is that it explains the complex relationships that exist between manifest variables and their overall effect through direct, indirect and total effects on energy consumption. Using the English House Condition Survey (EHCS) consisting of 2531 unique cases, the main drivers behind residential energy consumption are found to be the number of household occupants, floor area, household income, dwelling efficiency (SAP), household heating patterns and living room temperature. In the multivariate case, SAP explains very little of the variance of residential energy consumption. However, this procedure fails to account for simultaneity bias between energy consumption and SAP. Using SEM its shown that dwelling energy efficiency (SAP), has reciprocal causality with dwelling energy consumption and the magnitude of these two effects are calculable. When nonrecursivity between SAP and energy consumption is allowed for, SAP is shown to have a moderately negative effect on energy consumption but conversely, homes with a propensity to consume more energy have a higher SAP rating and are therefore more efficient.

Keywords: residential; energy; efficiency; structural; equation; modelling;

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[2] I would like to thank and acknowledge Dr Michael Pollitt and Professor Douglas Crawford-Brown for their feedback on this paper.

1.0 Introduction

Buildings are a significant contributor to greenhouse gas emissions with space heating alone responsible for over half of all end use emissions from UK dwellings (WWF 2007). In 2007, the UK government put in place a National Energy Efficiency Action Plan (NEEAP) to reduce emissions from the UK housing stock by 31% on 1990 levels by 2020. More recently, the government's own Climate Change Act (UK Government 2008) sets a legally binding target to reduce greenhouse gas emissions by at least 80% on 1990 levels by 2050. It is recognised that meeting such a target will only be possible through radical reductions in energy consumption and necessary but strategic changes to energy supply and delivery. In addition, the residential sector has been repeatedly identified by government departments (WWF 2007; Communities and Local Government 2006; DECC 2009; Energy Efficiency Partnership 2008; Great Britain. 2007); commercial organisations (Mckinsey 2008; McKinsey 2009), non governmental organisations (Centre for alternative technologies 2007; WWF 2007) and by academia (ECI 2005; Levine & Urge-Vorsatz 2008; World Business Council for Sustainable Development 2009) as having one of the lowest costs and largest impacts for reducing CO_2 emissions. Still, there remains significant debate about the best approach for reaching the CO_2 reductions imminently required. Moreover, there is insufficient empirical research quantifying the complex relationship between major driving forces purporting to explain residential energy consumption and in particular, the contribution that increasing building efficiency can have on reducing energy consumption.

1.1 Contribution

This paper presents the first known application of structural equation modelling (SEM) for the explanation of residential energy consumption in England. This powerful statistical technique allows for the calculation of both direct and indirect effects that explain energy consumption in the residential sector. For example, household (HHLD) income is directly correlated with energy consumption but is also indirectly correlated and mediated through dwelling floor area. This is because homes having a high income tend to have a larger floor area and therefore require more heating. Using SEM it is possible to decompose the relative magnitude of these effects and therefore gain deeper understanding for what variables can have the most effect at reducing residential energy consumption. With this technique it is also possible to show the relative sensitivities of different explanatory variables on residential energy consumption. Sensitivity analysis is important for identifying leverage points within the system. In addition, this research presents new evidence to quantify the extent that SAP has on reducing residential energy consumption. More importantly, empirical proof is provided showing a reciprocal relationship between SAP and energy consumption, and that, ceteris paribus; dwellings with a propensity to consume more energy will have, on average, higher SAP ratings. However, the reverse is also true and dwellings with high SAP values will have, ceteris paribus, reduced energy consumption owing to increased efficiency. Finally, these two effects are separately and empirically calculated.

1.2 Structure of paper

The first section of this paper presents important recent developments in the state-of-the-art in residential energy modelling. A thorough review of the literature has shown a serious lack in recent years in the development of bottom-up statistical models for explaining the driving forces behind residential energy consumption and particularly the measured benefits of energy efficiency improvements. In order to tackle this problem, a structural equation model is introduced with an emphasis on how this relatively modern statistical technique can be applied and used to provide deeper insight into understanding the cause and effect relationships behind residential energy consumption. What follows is a description of the dataset and how the variables were prepared prior to analysis. The importance of SEM for conducting this type of analysis is highlighted by the results obtained from a simple multivariate regression, a technique unable to measure non-recursivity or easily distinguish direct and indirect effects. Statistical results are presented before leading into a discussion on the main findings and the implications this research may have for policy makers.

2.0 The epistemology of residential sector energy modelling

2.1 Energy demand modelling in the residential sector

Over the last two decades there has been a plethora of national level domestic energy models that vary in data requirement, disaggregation level, socio technical assumptions and the type of scenarios or predictions that can be made (Kavgic et al. 2010). This brief literature review is intended to provide an overview of the major epistemic approaches that have previously been used for modeling residential energy consumption and emissions in the UK. Due to the fact that several relatively recent publications provide excellent reviews on different residential sector modelling techniques, this section has purposefully been kept brief (Tso & Yau 2007; Swan & V. Ismet Ugursal 2008; Strachan & Kannan 2008; McFarland et al. 2004; Kavgic et al. 2010; Jebaraj & Iniyan 2006; Aydinalp-Koksal & V. Ismet Ugursal 2008; Böhringer & Rutherford 2009; Tuladhar et al. 2009).

Since the advent of computers many national level models have been developed to assist in the prediction and analysis of domestic energy consumption. Most authors agree that the majority of models generally take two broad epistemic approaches described as being either top-down or bottom-up. Advances in recent years have seen the development of sophisticated hybrid models that integrate both of these approaches into a single model. In parallel with these integrated techniques, a number of advances have been made in machine learning, new statistical approaches and GIS methods (R. Rylatt et al. 2003) capable of modelling the interaction between energy, economy, environmental systems and technology in the built environment. For example, a neural-network based national energy consumption model has been developed for the Canadian residential sector (Aydinalp et al. 2003) and other innovative statistical techniques such as decision tree analyses are being used to model residential energy consumption at the national level in Hong Kong (Tso & Yau 2007).

2.2 Top-down modelling

Modelling energy demand using the top-down approach uses macroeconomic principles and the interaction between energy consumers and the economy at large, relying on aggregate economic behaviour based on observed historic trends to predict future changes in energy. Top-down methods use econometrics and multiple linear regression methods for the explanation of variance between dependent and independent covariates. For example, econometric top-down models use aggregate level data such as income, fuel prices and average dwelling efficiency to explain the variance of aggregate energy consumption from the residential sector. Such models are often criticised for lacking detail about present and future technologies with an inability to allow for future events when environmental, social and economic conditions may be entirely different from what was experienced in the past (Kavgic et al. 2010). Even more importantly, these models tend to neglect the socio-technical and behavioural considerations of energy use at the disaggregated household level and instead make more general conclusions about aggregate or average energy consumption. As argued by Hitchcock (1993) energy consumption patterns are a complex technical and social phenomenon and in order to be understood appropriately must be tackled from both engineering and social science perspectives concurrently.

Several models have been developed that implement top-down regression methods for modelling aggregate residential energy demand from the UK residential sector (A. J. Summerfield, Lowe & Oreszczyn 2010a; Les Shorrock 2003; Azadeh et al. 2010). One of the first top-down regression methods was developed by the Building Research Establishment (BRE) and uses the domestic energy fact file (DEFF) to predict aggregate housing stock energy consumption. The obvious limitations of this method include the homogenous treatment of the UK dwelling stock with a limited number of independent variables averaged over the UK on an annual basis. Although the power of the model to predict total energy consumption from the domestic sector appears robust when compared with historical trends, the model cannot isolate regional, local or individual household effects. It also fails to isolate important explanatory variables that may have an effect on energy consumption such as fuel type, growth in appliances, changes in relative wealth and energy costs. Thus it does not explain consumption in sufficient detail to quantify the effects of different policy measures (Kavgic et al. 2010). On the back of the DEFF model an improved version was created using decomposition analysis to explain the various factors contributing to CO_2 emissions between 1990 and 2000 in the UK residential sector (Les Shorrock 2003). More recently, the model was improved again (A. J. Summerfield, Lowe & Oreszczyn 2010a) by adding inflation adjusted energy price to the equation thus creating the annual delivered energy and price model (ADEPT). The model still suffers from the same limitations of the DEFF model, and similar to other aggregate regression models cannot explain the consumption characteristics at the household level nor model the specific effects of technologies, policy options or behaviour.

2.3 Bottom-up modelling

Although aggregate regression methods help to show trends in total dwelling stock energy consumption patterns, they cannot explain the various components that contribute to energy consumption at the household level. For this type of analysis it is necessary to conduct investigations at the micro-level. Bottom up methods take a disaggregated approach and estimate energy demand and emissions using high resolution data using a combination of physical, social, behavioural and demographic properties for a household (Hoogwijk et al. 2008; Johnston 2003). The empirical data requirement for bottom-up models is significantly more demanding requiring large, high-resolution datasets that contain specific characteristics for each dwelling that include physically measured variables, demographic information and sometimes even details about energy consuming behaviour (BRE 2005). With bottom-up methods it is also possible to combine, or aggregate micro-level data in order to generate new variables that provide information about the total dwelling stock.

Two types of bottom-up methods can be identified and are contingent on the data and structure of the analysis required. These are the engineering method and the statistical method. The engineering method uses a sample of houses and technologies to represent the national housing stock. In this approach thermodynamic equations are employed to balance the energy requirements of a dwelling. Such models therefore require physically measurable variables such as information on different building components (floors, roofs, walls, windows etc) building type, building location and the efficiency and type of heating systems in operation. Given the modeller has access to a sufficient level of empirical data on the physical properties of a building and has well grounded assumptions on the type of heating and behavioural patterns associated with a buildings operation; it suggests it is possible to estimate the energy consumption and emissions for a building. Due to the fact that estimations are conducted at the micro-level, such models therefore have the potential to model the impact of various policy and technology options for carbon mitigation. Unlike top-down methods, bottom-up methods allow assessment for the effects of new technology options and the penetration of different technologies into the building stock.

The complexity of a building stock model depends on the underlying engine used for the calculation. In the UK for example, BREDEM (Building Research Establishments Domestic Energy Model) is the most widely used model for calculating the energy requirements of a domestic building. The model itself uses a series of heat balance equations and forms the basis of the Governments Standard Assessment Procedure (SAP) used for the energy rating of dwellings (BRE 2005). One major weakness of building physics models are the assumptions made regarding the behavioural factors that contribute to energy consumption, which are known to be significant (ECI 2005, p.57; Hitchcock 1993). Another failing of physical models is their general lack of allowance for economics and as a consequence a failure to describe and account for the purchase of different energy technologies in the home and the more general behavioural choices made by households (Jamasb & Meir 2010; Brutscher 2011; Haney et al. 2010).

Similar to top-down methods, regression techniques can also be used at the micro-level. A process known as Conditional Demand Analysis (CDA) was developed by Parti and Parti (1980) as a robust statistical method for understanding how final energy is consumed in the home by technology type and is thus useful for creating domestic load profiles. CDA is now widely recognised as a robust statistical method for estimating the load profiles of different household appliances without the need for individual appliance monitoring (Larsen & Nesbakken 2003; Aigner et al. 1984; Fiebig et al. 1991; Perron & Lafrance 1994; Aydinalp et al. 2003). Although the use of CDA allows for the allocation of energy consumption between different household appliances it does not explain or predict what household energy consumption might be, nor is this method capable of modelling the change in building characteristics or technologies over time. This method also suffers from multicollinearity problems making it difficult to isolate energy use of highly saturated appliances such as washing machines and televisions.

2.4 Bottom-up econometric methods

More in line with the research presented in this paper are bottom-up econometric methods, largely neglected in reviews on residential energy modelling. Furthermore, there is a large gap in the number of bottom-up econometric models that can be used to identify the factors that purport to explain energy consumption at the household level in the UK. While one or two models were developed in the 80’s and 90’s using large statistically powerful datasets (P. Baker et al. 1989) the full potential of these models was never realised. Models more recently developed rely on data obtained from very small-localised datasets representing just a small subset of the population with, perhaps, a few hundred representative cases (K. J. Baker & R. M. Rylatt 2008). The main reason for this significant gap in the literature can be explained by a serious lack of statistically significant, high quality, high resolution data combining household level energy consumption data with dwelling characteristics and user behaviour collected at the national level. Indeed, there are many benefits of Multiple Linear Regression (MLR) techniques over other methods including their simplicity and adaptability to almost any problem. A downside of this approach is the assumption that a single dependent variable is a linear function of multiple independent variables. It is also difficult to ascertain the underlying causal mechanism behind the model as standard multiple regression techniques only provide evidence of correlation and therefore can sometimes suffer from multicollinearity. As shown in this paper, structural equation modelling is a robust, well known statistical method and when applied to the residential sector is able to provide new insight and overcome many of the weaknesses and pitfalls of these other methods.

3.0 Methodology

3.1 The dataset

The model is based solely on publicly available data and comprises information available from two principle datasets: The 1996 English House Condition Survey (EHCS) and the 1996 Fuel and Energy Survey (FES). The EHCS is conducted every five years and is the only survey to provide thorough data on the condition of the national housing stock (DETR 1996). The 1996 EHCS consists of 12,131 real cases, and the sample is selected to represent the dwelling stock in England. Usually the EHCS focuses primarily on the physical condition of dwellings and other building characteristics with limited scope for other demographic and economic information. In 1996 however, a supplemental FES was carried out on a subsample of 2,531 cases of the EHCS. Importantly, the FES subsample includes metered electricity and gas consumption data, information on energy usage as well as data on energy expenditure. The interviews were conducted from January to May 1996, with the fuel survey collecting actual energy and fuel usage over eight consecutive quarters. Thus information on a dwelling's physical condition, the economic status of its inhabitants as well as demographic and behavioural information can all be used in an analysis to determine what factors may explain residential energy consumption. A similar survey of this scale and type has not been completed in England since 1996 but one is planned for the end of 2011 (Communities and Local Government 2010).

The relevance of this data for solving the problems of today can be emphasised in several respects. Firstly, one strength of the approach adopted here is that it develops a structural relationship between model variables. In the residential sector such relationships are grounded in physical laws and defined by economic relationships. For example, homes with a large floor area will take more energy to heat and homes having higher incomes will be more likely to spend more money on heating. For this reason, structural relationships estimated from historical data are still relevant for understanding consumption today and in the future. This is because, although the values of these variables may change substantially over time, the structural relationship between the variables will remain relatively stagnant. An unfortunate symptom of the residential sector is its inherent underlying inertia and the significant time required to make any meaningful changes. For example, the average SAP value of dwellings surveyed in the EHCS went from 44 in 1996 to 51 in 2007.

3.2 Explanatory Variables

The EHCS and FES are two large national housing surveys in England. They cover all tenure types and involve a physical inspection of the property by certified professionals. Included in the dataset are hundreds of variables that measure almost every physical property of the dwelling and demographic characteristics of the occupants. Several previous studies have used this information to gain valuable insight into energy and emissions (Dresner & Ekins 2006; LD Shorrock & Dunster 1997; Firth et al. 2010). Armed with such information it is possible to develop a model consisting of an enormous number of variables pertaining to explain residential energy consumption. However, in

SEM, as it is in science more generally, parsimony is highly valued. If two explanations for a phenomenon are equally good, then the more parsimonious explanation is the preferred option. With this in mind, variables were chosen on the premise that they were likely to explain a large proportion of the variance in energy consumption. If the addition of a variable to the model performed just as well as the simpler, more parsimonious model, the new variable was discarded in favour of the more parsimonious model. The following variables were chosen due to their known relevance of explaining residential energy consumption.

Number of occupants is the number of people living at the dwelling at the time the survey was conducted.

Household Income is the annual net income for the household after tax and national insurance contributions have been deducted.

Floor Area is the internal useful floor area for the dwelling and excludes integral garages, balconies, stores accessed from the outside and the area under partition walls.

SAP is the UK Governments standard assessment procedure for measuring the energy efficiency of dwellings. The values in this dataset were calculated using the 1996 SAP calculation procedure and were derived by the Building Research Establishment (BRE), the organisation responsible for managing SAP for the UK Government. In this analysis, values range from 0-110 with low values indicating poor dwelling efficiency.

Temperature Difference is the difference between the internal living room temperature and the outside temperature at the time the survey was conducted.

Energy Pattern is a scale from 0-5 describing how frequently the occupants heat their home. Each question requires a binary response from which a scale can be constructed. A zero value means the respondent answered negative to all questions while a value of five means the respondent answered positively to every question.

- Is the bedroom heated on the weekend?
- Is the bedroom heated during the week?
- Is the living room heated on the weekend?
- Is the living room heated during week?
- Is the home heated during the week and throughout the day?

Dwelling Energy Expenditure was collected over eight consecutive quarters and taken with permission from the energy supplier of the dwelling. Average annual energy expenditure is then calculated and used in the model.

The age of the head of the household is a categorical indicator representing six age groups from 16 to 65 and over.

Degree days is a measure of the temperature difference between the outside temperature and a base temperature of 18.5° Celsius and the length of time this temperature persists over a period of a year.

The following dummy variables were also tested:

Urban dummy is a binary indicator for the location of the dwelling (Communities and Local Government 2005, p.28).

Owner dummy is a binary number indicating whether the occupier owns the dwelling.

Economic status dummy is a binary indicator for the employment status of the head of the household.

Energy prices were also considered as an important driver for explaining residential energy consumption. As this study used a cross-sectional analysis, it was not possible to control for the effect of energy prices on energy demand. As shown by Summerfield (A. J. Summerfield, Lowe & Oreszczyn 2010b), energy prices in the UK are relatively inelastic with an estimated elasticity of -0.20. This means a 50% increase in energy price will lead to an approximate 10% decline in energy demand. Similar results were found by others (Hunt et al. 2003; Micklewright 1989) with most studies finding elasticities in the range -0.05 to -0.50 (Fouquet 1995; Boonekamp 2007; Lijesen 2007).

Table 1 lists the descriptive statistics for the variables used in the model.

Table 1: Descriptive statistics for model variables

	Minimum	Maximum	Mean	Std. Error[1]	Std. Deviation[1]
Number in household	1.00	10.00	2.51	0.04	1.35
Floor Area (m^2)	20.0	252.4	81.3	0.97	31.2
HHLD Income (£)	2,340	103,825	15,317	315	10,072
SAP Rating	0	109	44.4	0.49	15.6
Annual Energy Expenditure (£)	74.2	3332	642	8.87	284
Living room temperature (°C)	0.3	36.9	19.0	0.09	2.79
Outside temperature (°C)	-9.2	39.1	6.90	0.15	4.75
Temperature Difference (°C)	-20.0	27.1	12.1	0.16	5.02
Energy Pattern (categorical)	1.0	5.0	3.15	0.04	1.24
Degree Days (categorical)	1749	2367	2089	6.25	200
Urban_Recode (dummy)	0	1	0.81	0.01	0.39
Owner of house (dummy)	0	1	0.69	0.02	0.46
Economic Status (dummy)	0	1	0.57	0.02	0.45
Age of head of household (categorical)	1	6	3.95	0.05	1.57

1. Std.Error and Std.Deviation calculations were calculated from the re-calibrated effective sample size of (n_c = 1025).

3.3 Preparing the data for analysis

The final dataset was created by combining the 1996 EHCS with the 1996 FES subsample using a field code common to both datasets. After the datasets were combined the final sample contained 2,531 cases. The sum of grossing weights equates to 19.265 million and represents the number of residential buildings in England in 1996.

3.4 Dealing with outliers

Datasets that contain univariate or multivariate outliers have the potential to significantly distort statistics leading to both Type I and Type II errors. Histograms and box and whisker plots facilitated the detection and deletion of a very small number of univariate outliers. Histogram plots of HHLD Income, Floor Area and Energy Expenditure revealed long right-hand tails with potential to adversely affect model results. The distributions of these variables were therefore truncated to five standard deviations from the mean. Multivariate outliers were found using Cook's distance and the Centred Leverage statistic but were found unproblematic after the univariate outliers had been removed.

3.5 Missing data

Missing data in substantive research is common (Lee 2007, p.355) and can be problematic for structural equation modelling if not handled correctly (Tabachnick 2007, p.61). A well-recognised statistical benchmark suggests datasets with missingness less than 5% to not be a problem (Kline 2005; Rubin 1976). Within this dataset, no single variable had less than 5% missing data and was therefore not considered a problem to conduct further statistical tests. The Expectation Maximisation (EM) method was chosen to replace missing values in the dataset (Schumacker & Marcoulides 1996).

3.6 Applying Sample Grossing Weights

Sample weights are defined as the application of a constant multiplying factor to data to vary the contribution that entry can make to the overall estimates. As shown by Dorofeev (2006, p.45) little has been published on the subject of weighting and is generally ignored in texts on statistics and survey research. Dorofeev (2006, p.45) shows that statistical procedures conducted on a sample without applying the grossing weights prior to the analysis may lead to incorrect inferences about the population including underestimation of standard errors of estimators leading to inflated Type I and Type II errors as well as erroneous model diagnostics. Grossing weights as they are used in the EHCS incorporate expansion factors which mean the sum of the weights represents the size of the population.

The EHCS and FES are large complex stratified surveys designed with *a priori* weighting designed to efficiently represent the dwelling stock of England. Each case in the sample is associated with a grossing weight derived from a stratified multi-stage cluster sampling process and calibrated to auxiliary variables subject to survey non-response adjustments. This is to allow for accurate analyses of particular groups of dwellings. For example, the sample size for particular groups of dwellings such as local authority dwellings, unfit dwellings and RSL dwellings need to be sufficiently large to provide a statistically significant sample. In order to maximise the efficiency of data gathering while still achieving statistical significance, survey stratification is needed. This technique requires over representation of small groups of dwellings and under representation of common groups of dwellings in the sample. Grossing weights are then applied to the final dataset to undo the effects of stratification and for the dataset to accurately represent the population. The post-weighted dataset, after adjustments are made for non-response and response bias should therefore be an accurate reflection of the population. If grossing factors are not taken into account, the final results will not be accurate or meaningful at the national level and therefore bias towards groups that have been unequally sampled.

The overall effect of applying weights is increased accuracy of model estimates and therefore reduced bias. However, this comes at the expense of precision (Dorofeev 2006). This is because weighting involves a substantive increase in the standard error of estimates, thus introducing wider confidence intervals and a loss of discrimination in significance testing. The loss in precision is directly proportional to the range in weights being applied to the sample, the greater the range in weights the greater the loss in precision. For any weighted sample the overall loss in precision can be obtained by calculating the "effective sample size" given by n_c in Equation (1.1). The ratio of actual sample size to effective sample size is known as the Weight Effect (WE) and is typically greater than 1.0 for weighted samples. Therefore the actual standard error (or confidence interval) of an estimate like the mean, $\overline{x}$, can be calculated by multiplying the actual estimate by the weight effect and therefore the standard error of an estimate can be expressed by Eq (1.3).

$$n_c = \frac{\left(\sum_{i=1}^{n} w_i\right)^2}{\sum_{i=1}^{n} w_i^{2}} = 1,025 \tag{1.1}$$

Hence,

$$WE = \frac{n}{n_c} = \frac{2,531}{1,025} = 2.47 \tag{1.2}$$

$$s.e(\overline{x}) = \sqrt{WE}\,\frac{S}{\sqrt{n}} = \frac{S}{\sqrt{n/WE}} = \frac{S}{\sqrt{n_c}} \tag{1.3}$$

Where, n_c, is the calibrated sample size, S, is the standard deviation of the original variable x from the post weighted calibrated sample, and n is the original un-weighted sample size. The result of using the calibrated sample size, n_c, has the same effect of reducing the sample size by $1/WE$ and therefore has the overall effect of increasing standard errors. Not applying the weighted sample correction factor will lead to incorrect computation of variance and margin of error calculations of the model estimates.

3.7 Testing for normality

Critical deviation from normality was tested for all model variables, including the use of frequency histograms. Model results from the untransformed dataset were compared against results for each dataset containing a transformed variable. Differences in the output for all transformed datasets were insignificant and therefore it can be concluded that the model is robust to minor deviations from normality.

4.0 Structural Equation Modelling

Structural equation modelling otherwise known as simultaneous equation modelling with latent variables owes its origins to both exploratory factor analysis (EFA) (Charles Spearman, 1904) and path analysis (PA) (Sewell Wright 1921). Wright's major contribution was to show that correlations among variables could be related to the parameters of a model represented by a pictorial path diagram with a capacity to indicate both correlated and causal relationships (Kaplan 2009, p.3). He also showed how such a representation could be used to estimate direct, indirect and total effects through intermediary or mediating variables(Lee 2007, p.15). Structural equation models are therefore able to provide new levels of insight previously unachieved with other more common techniques.

SEM subsumes both exploratory factor analysis and path analysis. In addition, SEM subsumes analysis of variance methods (ANOVA), multiple linear regression (MLR) and canonical analysis (CA). Given the scope of problems that can be solved using SEM, its power as a statistical tool for solving complex real world problems is clear. The mathematical foundations of SEM rely largely on the principles developed for ANOVA and MLR and therefore many problems easily handled using SEM can also be solved using ANOVA or MLR however, the process becomes overly complicated rather quickly. With SEM this difficulty is obviated, where the natural focus is not on direct effects, as it is in MLR, but on indirect and total effects, where total effects are the sum of direct effects and indirect effects (Keith 2006, p.213). As argued by several authors (Keith 2006; Kline 2005) structural equation modelling is a better choice for explanatory analysis of non-experimental data and provides a clearer representation of the relationships between variables through a pictorial diagram. At the most basic level SEM's are a type of factor analysis and can therefore be viewed as a form of exploratory data analysis (EDA) where the number of factors, factor loadings and rotation of the factor loading matrix are determined through exploratory analysis (Lee 2007).

Today it is common practice to enlist the power of specialised computer software (Keith 2006, p.212). Today, there are many computer programs specifically developed to solve SEM's including: AMOS, Mplus, EQS, Mx Graph, RAMONA and SEPATH. The analysis presented in this paper was completed using AMOS (Analysis of Moment Structures) which is a supplementary program bundled with PASW statistics. For detailed mathematical derivation of SEM see the following textbooks (Kaplan 2009; Blunch 2008; Kline 2005; Tabachnick 2007)

Structural equation models allow both confirmatory and exploratory modelling, meaning that such models can be used for both theory testing and theory development. In this paper a more confirmatory approach is adopted in order to substantiate the explanatory power of different variables and their effect on household energy consumption. From here it is possible to test the hypothesis that SAP and household energy consumption have reciprocal causality otherwise known as nonrecursivity.

5.0 Model development

Based on substantive prior research a structural equation model was developed to represent the expected underlying causal relationships likely to explain domestic energy consumption in England. This is represented in pictorial form as a path diagram. The model developed is based on the premise that domestic energy consumption can be explained by several manifest variables. Using such a model it is possible to test a number of hypotheses about the explanatory power and statistical significance between model variables and what their relative effect on residential energy consumption might be.

Before presenting more detailed analysis it is prudent to first explain the different components that constitute path diagrams. Rectangles represent measured variables also known as manifest or indicator variables while circles or ellipses represent unmeasured or latent variables. Single headed arrows show direct causation in the direction of the arrow between two variables. Importantly, the underlying data used by the model is not used in any way to make inferences about the direction of causality. A researcher armed with such prior knowledge about the variables under question is thus only able to infer *weak causal ordering* to the underlying structural relationship between variables (Keith 2006, p.215). For example, in Figure 1 when an arrow is drawn from Floor Area to Energy Expenditure it does not show that Floor Area causes higher energy consumption it says that *if* Floor Area and Energy Consumption are causally related it is likely to be in the direction of the arrow and not the reverse. The explanatory power of the causal relationship is provided by the regression weight and is usually drawn on the line between the two variables. Double headed arrows represent correlations between variables and do not imply causality. Endogenous variables are variables that are defined by other variables and are therefore identified as having at least one single headed arrow feeding into them (e.g. Floor Area, Temperature Difference, HHLD Income and Annual Energy Expenditure). Exogenous variables are only used to define other variables in the model and therefore only have arrows that lead to other variables (e.g. Number of occupants and Energy Pattern). All endogenous variables must have a disturbance or error term that represents the unexplained variation in the variable not accounted for by other variables, this also includes measurement error. Exogenous variables may also include a disturbance term but this is not a necessary component. Using a path diagram it is possible to represent the model as a system of simultaneous regression equations.

5.1 Importing the dataset into AMOS 18.0

A major benefit of using AMOS 18.0 is the ability to import the correlation matrix of the dataset as opposed to the entire sample for solving the model. As AMOS 18.0 does not allow for unequal weights to be used during model estimation it was necessary to import a post-weighted correlation matrix into AMOS 18.0. The benefit of using this approach is that grossing weights could be correctly applied to represent the calibrated sample size, n_c, before being used to produce the correlation matrix (Table 3) thus ensuring that variance and standard error estimates are correctly calculated for the sample being used.

5.2 Model identification and non-recursivity

Ensuring the degrees of freedom *(dof)* within the model are equal to or larger than the number of parameters to be estimated is a necessary but insufficient condition for identification. In SEM over-identification is preferred as over-identification allows for the evaluation and overall quality or fit of the model. The second condition that must be met is empirical identification and requires the data being used on the model to produce semi-positive definite matrices.

The addition of feedback loops in SEM automatically introduces non-recursivity thus making the model more difficult to solve due to the added restrictions placed on the model. One assumption for non-recursive models is the assumption of stationarity, requiring the causal structure of the model not to change over time. For cross-sectional data, like the one being used for this analysis, there is also the assumption of equilibrium. This means that any changes in the system underlying the feedback relationship have already manifested and the system has reached a steady state (Kline 2005, p.239). The structural equation model developed here satisfies both of these conditions. Firstly, the stationarity assumption is satisfied because the causal effects of residential energy consumption do not substantially change over time. Secondly, the variables identified are long lasting and slow to change (number of occupants, floor area, income etc) and therefore the effects of these indicators are assumed to manifest on energy consumption over many years prior to the survey being taken. For example, people living in homes with a high household income have a degree of familiarity with receiving a high income and therefore Income effects on energy consumption would have already manifested in the home prior to the survey being taken and therefore can be assumed to have reached equilibrium.

5.3 Model precision and confidence intervals

Estimating model parameters is only part of the solution. Checking the precision and accuracy of the model is necessary if one is to have any confidence in the results. This requires the calculation of standard errors and confidence intervals for each model parameter. In this section a bootstrapping method is introduced for assessing the precision that can be obtained from the model and underlying data.

5.4 Weighted Random Sampling with Replacement

Previously, the estimation of the model was achieved by directly importing the correlation matrix from the post-weighted sample into AMOS 18.0. However, there are several alternatives for estimation using a weighted dataset in AMOS 18.0. One such method is to use well-understood sampling procedures to create a new subsample from the original dataset. This method is known as weighted random sampling with replacement (WRSWR). It is a probabilistic sampling method where the grossing weights for each case represent the probability a case is selected and added to the subsample. Suppose that w_i are the grossing weights produced by the complex sample design, the probability that case i is selected from the sample is then given by $P(X_i = x) = w_i / \sum w_i$. Each time a case is selected it is replaced back into the sample at which point a new case is selected and saved in the new sample. Repeating this process N times creates a new sub-sample representative of a post-weighted sample. Similar to bootstrapping, the new sample will contain some cases that are repeated multiple times while other cases will not be represented at all. Because case selection is based on weighted probability it simulates the effect of selecting a case at random from the population and therefore the subsample represents a post-weighted sample of the population. Importing a representative dataset into AMOS 18.0 rather than the correlation matrix allows for deeper statistical analysis such as bootstrapping.

5.5 Bootstrapping

A key advantage of AMOS 18.0 is the functionality to perform bootstrapping on the model from the imported dataset. With bootstrapping it is possible to determine empirical estimates of standard errors of any parameter, even standard errors of standard errors (Keith 2006, p.258). In addition, with nonparametric bootstrapping it is not necessary to have data that fits to a normal distribution, thus prior transformation of the data is not necessary. In fact the only requirement is for the distribution of the sample to be the same basic shape as the distribution of the population. Confidence intervals for each of the model parameters are therefore calculable.

6.0 Results

6.1 Multiple Linear Regression

Before any structural equation model was developed a standard multiple linear regression model was created to understand how much of the variance in energy consumption could be explained using standard methods. Many national level domestic energy models rely on household efficiency indicators such as SAP to predict future domestic energy consumption. It therefore follows that SAP should be a good indicator and have statistically significant predictive power for estimating domestic energy consumption. In order to test this hypothesis an MLR model was employed Equation (1.4).

$$\mathbf{y} = A + B_1\mathbf{x} + B_2\mathbf{x} + B_3\mathbf{x} + B_4\mathbf{x} + B_5\mathbf{x} + \boldsymbol{\varepsilon} \quad (1.4)$$

Equation (1.4) measures the predictive power and statistical significance of SAP on energy consumption while controlling for several other important factors known to influence energy consumption. The results of this analysis are shown in Table 2.

Table 2: Mutiple Linear Regression diagnostics

	Unstandardised Coefficients		Standardised Coefficients		95.0% Confidence Interval for B	
	B	Std. Error	β	t-statisic	Lower Bound	Upper Bound
Intercept (A)	163.6**	0.262		624.9	163.0	164.1
SAP (β_1)	0.971**	0.003	-0.053**	-280.6	-1.0	-1.0
Number in household (β_2)	62.67**	0.043	0.297**	1447.4	62.6	62.8
Floor Area (m2) (β_3)	2.380**	0.002	0.262**	1214.5	2.4	2.4
HHLD Income (000's £) (β_4)	3.944**	0.006	0.140**	644.6	3.9	4.0
Temperature Difference (C) (β5)	2.390**	.011	.042**	221.5	2.4	2.4
Energy Pattern (categorical) (β6)	25.76**	.044	.112**	585.4	25.7	25.8

R^2 = 0.314, Adj R^2 = 0.314, Std. Error of Estimate = 235.1

*** statistically significant at p=0.05, ** statistically significant at p=0.01**

The null hypothesis for this experiment was that SAP is both statistically significant ($p < 0.01$) and correlated with energy consumption ($R^2 > 0.1$) after controlling for other covariates. As shown in Table 2 the model is reasonably well specified (Adj.R^2 = 0.314) and SAP is shown to be a statistically significant variable (p< 0.01). However, the power for SAP to predict energy consumption is lower than expected as shown by the small standardised regression weight, β (-0.053), indicating that only a small proportion of the variance in energy consumption can be explained by SAP. The result of this simple analysis brings into question the basic premise of many domestic energy models which rely on SAP measurements to accurately predict household energy consumption.

As the results from the MLR show, SAP performs less than expected as a predictor for HHLD energy consumption. This process however does not allow for reciprocal causality between energy consumption and SAP. A basic assumption of MLR regression is that the independent variables have a direct effect on energy consumption but also, the dependent variable does not have any effect on the independent variables. When both variables are thought to affect each other, the relationship is described as non-recursive or cyclical. Separating and quantifying two bi-directional effects is difficult but made possible utilising the properties of an over-identified non-recursive structural equation model.

The correlation matrix in Table 3 was created using the post weighted sample and the calibrated sample size, n_c.

Table 1: Correlation matrix of significant explanatory variables

Pearson Correlation	Energy Expenditure	HHLD Income	Floor Area	Number of Occupants	Temperature Difference	SAP	Energy Pattern	Degree Days
Energy Expenditure	1	0.375**	0.420**	0.452**	0.085**	0.031	0.188**	0.012
HHLD Income	0.375**	1	0.436**	0.475**	0.104**	0.110**	0.100**	0.013
Floor Area	0.420**	0.436**	1	0.352**	0.021	0.106**	0.109**	-0.004
Number of Occupants	0.452**	0.475**	0.352**	1	0.053	0.104**	.131**	0.004
Temperature Difference	0.085**	0.104**	0.021	0.053	1	0.034	.093**	0.123**
SAP	0.031	0.110**	0.106**	.104**	0.034	1	.084**	0.012
Energy Pattern	0.188**	0.100**	0.109**	0.131**	0.093**	0.084**	1	0.04
Degree Days	0.012	0.013	-0.004	0.004	0.123**	0.012	0.04	1

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

The results of the structural equation model are presented in Figure 1. Standardised regression weights are shown on each of the arrows connecting two indicator variables and represent the direct effects that one variable has on another variable. The standardised and unstandardised regression coefficients are also shown in Table 4 alongside the respective statistical tests for significance. A key advantage of using standardised regression coefficients is the ability to compare the relative magnitude of effects across variables.

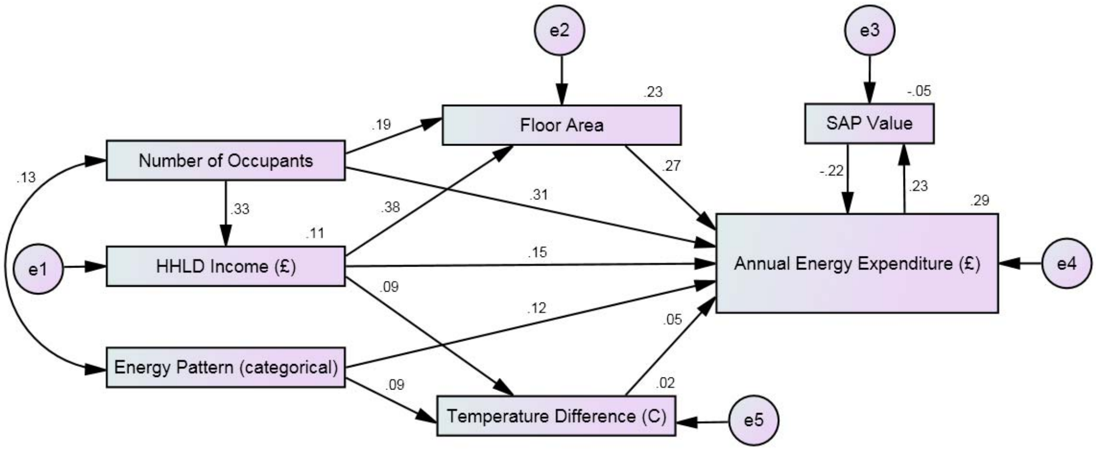

Figure 1: Structural Equation Model

Table 5 presents the standardised *indirect effects* each variable has on each related variable, and measures the effect of one variable on another variable through an intermediary variable i.e. HHLD Income effects Annual Energy Expenditure through the mediating variable of Floor Area. *Total effects* are simply the sum of the direct effects and the indirect effects of all variables that are shown to statistically explain the variation of that variable. The results for total effects are shown in Table 6. Tables 5 and 6 should be read as the column variable affecting the row variable.

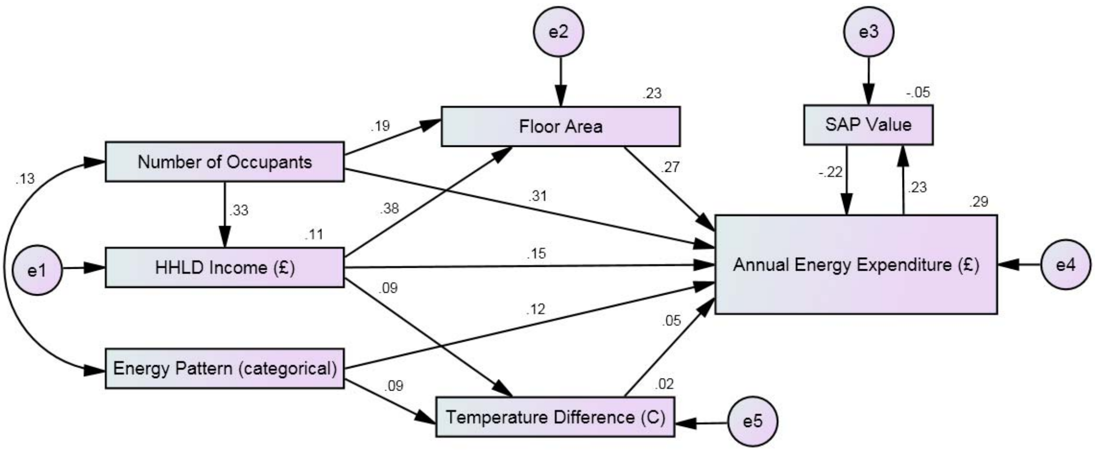

Figure 1: Structural Equation Model

Table 2: Standardised indirect effects

	Energy Pattern	Occupants	HHLD Income	Temperature	Floor Area	SAP Value	Annual Energy Expenditure
HHLD Income	0	0	0	0	0	0	0
Temperature	0	0.030	0	0	0	0	0
Floor Area	0	0.126	0	0	0	0	0
SAP Value	0.029	0.099	0.057	0.010	0.061	-0.048	-0.011
Annual Energy Expenditure	-0.002	0.113	0.095	-0.002	-0.013	0.010	-0.048

Table 3: Standardised total effects

	Energy Pattern	Occupants	HHLD Income	Temperature	Floor Area	SAP Value	Annual Energy Expenditure
HHLD Income	0	0.329	0	0	0	0	0
Temperature	0.087	0.030	0.092	0	0	0	0
Floor Area	0	0.314	0.381	0	0	0	0
SAP Value	0.029	0.099	0.057	0.010	0.061	-0.048	0.224
Annual Energy Expenditure	0.121	0.419	0.241	0.044	0.258	-0.206	-0.048

6.2 Other paths tested

A large number of other causal relationships between different variables were tested before arriving at the final solution as shown in Figure 1. These are referred to as nested models and defined as any model that can be derived from the initial model by deleting or adding paths between variables. Each path was systematically tested for significance and power. Paths not shown in Figure 1 were found to have no statistically significant causal effect within the model and therefore fixed to zero.

6.3 Testing for non-recursivity

In order to test for non-recursivity between SAP and Energy Expenditure it is necessary to test two competing, but nested models. When two models are nested it is possible to analyse the change in χ^2 to test for improved model fit. The model with one or more paths deleted is more constrained, has higher *dof,* and is therefore more parsimonious. To test whether the non-recursive, less parsimonious model is a statistically better fit it is necessary to calculate $\Delta\chi^2$ and $\Delta\,dof$ between the two models, this is shown in Table 3. Looking up $\Delta\chi^2$ and $\Delta\,dof$ in probability tables shows a related probability ($p<0.01$); indicating the additional path between Energy Expenditure and SAP resulted in a statistically significant increase in $\Delta\chi^2$. Not only does the more straightforward recursive model fit worse than the non-recursive model, but it fits statistically significantly worse. Even though the recursive model is more parsimonious it comes at too great a cost in terms of model fit. In conclusion, non-recursivity between SAP and Energy Expenditure is shown to be an important parameter in explaining residential energy consumption.

Table 4: Test for nonrecursivity in model

	χ^2	*dof*
Recursive model	25	9
Non recursive model	7.3	8
Difference	$\Delta\chi^2 = 17.7$	$\Delta\,dof = 1$

6.4 Variables analysed but not used by final Structural Equation Model (SEM)

Table 8 shows the statistical results corresponding to the variables not shown to explain Energy Expenditure or contribute to the statistical fit of the model. Each of the variables was added to the model and compared with the best fitting model. The only variable shown to be statistically significant was the variable indicating if the dwelling was built in a city (Urban Dummy). Unfortunately, with the addition of this variable the overall model fit statistics declined from (χ^2 = 7.3, RMSEA = 0.000, TLI = 1.00, AIC= 47.3) to (χ^2 = 52.9, RMSEA = 0.052, TLI = 0.909, AIC = 96.9) and therefore this variable was also dropped from the final model as it lowered overall model fit.

Table 5: Unused variables

			Standardised Coefficients	Unstandardised Coefficients		Significance		
			β	B	Std.Err	C.R.	P(sig.)	Label
Annual Energy Expenditure	<---	Age of Head Occupant	0.026	4.7	5.4	0.86	.39	-
Annual Energy Expenditure	<---	Economic Status (dummy)	-0.015	-8.8	17.9	-0.50	.62	-
Annual Energy Expenditure	<---	Owner Occupier (dummy)	0.030	18.3	18.2	1.00	.32	-
Annual Energy Expenditure	<---	Urban (dummy)	0.093	67.2	19.6	3.4	***	-
Annual Energy Expenditure	<---	Degree Days	0.004	.0054	.038	0.14	.89	-

6.5 Results from bootstrapping exercise

Bootstrapping allows the calculation of standard errors and therefore confidence limits of the statistics of interest. Table 9 shows the upper and lower bounds for both the standardised and unstandardised direct effects in the model. Note the similarity in regression weights from the bootstrap to those regression weights obtained from the method where the correlation matrix was used for the analysis. This shows the correlation matrix method and the post-weighted subsample selection method compare well with one another.

Table 6: Upper and lower bounds calculating from bootstrap estimates

			Standardised Coefficients			Unstandardised Coefficients		
			β	Lower	Upper	B	Lower	Upper
HHLD Income	<---	Occupants	0.335	0.320	0.356	2538	2402	2692
Floor Area	<---	Occupants	0.193	0.174	0.213	4.52	4.09	5.02
Temperature	<---	Energy Pattern	0.107	0.090	0.129	0.425	0.357	0.512
Floor Area	<---	HHLD Income (000's)	0.387	0.369	0.402	1.199	1.141	1.253
Temperature	<---	HHLD Income (000's)	0.095	0.078	0.116	0.046	0.037	0.056
Annual Energy Expenditure	<---	Occupants	0.302	0.284	0.320	64.071	60.0	68.2
Annual Energy Expenditure	<---	HHLD Income (000's)	0.130	0.114	0.151	3.655	3.222	4.272
Annual Energy Expenditure	<---	Energy Pattern	0.120	0.107	0.140	27.680	24.5	32.3
Annual Energy Expenditure	<---	Floor Area	0.297	0.275	0.314	2.692	2.51	2.86
Annual Energy Expenditure	<---	Temperature	0.039	0.0211	0.0553	2.264	1.23	3.21
Annual Energy Expenditure	<---	SAP Value	-0.212	-0.249	-0.184	-3.899	-4.55	-3.38
SAP Value	<---	Annual Energy Expenditure	0.227	0.197	0.262	0.012	0.011	0.014
Occupants[4]	<-->	Energy Pattern	0.231	0.199	0.261	0.139	0.120	0.156

1. Bootstrap confidence intervals are based on the bias-corrected percentile method.
2. Estimates are based on the bootstrap sample size (10,000 cases)
3. Confidence intervals are calculated at the 95% level
4. Covariances are listed under standardised estimates while correlations are listed under unstandardised estimates.

6.6 Model fit statistics

Identifying and using model fit indices in SEM's remains greatly debated. There is still no general agreement on the form or type of fit indices that should be used to measure model integrity. The development of different indices has been motivated, in part, by the known sensitivity of the χ^2 statistic to large sample sizes. Consequently, most literature suggests a selection of fit-indices need to be presented with SEM results (Vernon 2007) as shown in Table 10, all indices show an extremely good fit of the model to the data and therefore we have confidence that the model itself could have produced the underlying data.

Table 7: Model fit indices

	N	*dof*	χ^2	P-value	GFI	PGFI	TLI	CFI	RMSEA	SRMR	Stability Index
Correlation method	1025	8	7.30	0.504	0.998	0.285	1.00	1.00	0.001	0.016	0.048

The degrees of freedom parameter (*dof*) is calculated as the number of distinct sample moments (28) minus the number of distinct sample parameters to be calculated (20) and therefore measures the degree to which the model is over identified. In SEM the null hypothesis (H_0) is that the model to be tested is unlikely to be due to chance and the alternative (H_a) is that it is not. The χ^2 statistic and its p-value therefore measure the probability that the model fits perfectly to the population. Therefore, if χ^2 is not statistically significant (p-value > 0.05) then we can not reject the null-hypothesis that the model is accurate and we therefore have evidence that the model may explain reality. As shown in Table 7, χ^2 is large with a p-value > 0.05, therefore we have evidence the model may be a good representation for the structural relationships in the population.

The Goodness of Fit Index (GFI) is analogous to R^2 in MLR and provides an estimate for the amount of covariance accounted for by the model. PGFI is simply a parsimony adjusted value for GFI. Two similar indices are also listed, the comparative fit index (CFI) and the Tucker-Lewis Index (TLI) and they compare the fit of the existing model with the null-model. TLI makes a slight adjustment for parsimony but all four indexes, and particularly PGFI, are adversely affected by sample size, though much less than χ^2. For all three, values over 0.95 suggest very good fit of the model to the data while values over 0.9 suggest an adequate fit. The Root Mean Square Error of Approximation (RMSEA) is a measure of the error of approximation, with values below 0.05 suggesting close fit and values under 0.08 suggesting a reasonable fit (Keith 2006, p.269). The standardised root mean square residual (SRMR) is among the best fit indexes and is a measure of the mean absolute value of the covariance residuals (Kline 2005, p.141). Perfect model fit is indicated by SRMR = 0 and values under 0.1 are generally considered favourable. In addition, non-recursive models have a further statistic that measures the stability of the model. This is known as the stability index and should be used only after equilibrium has been shown to exist on rational grounds. Values below 1.0 are thought to indicate a stable model. In summary, all model fit indices indicate that the model under analysis may be used to approximate reality and that the model and data are consistent.

6.7 Discussion

Many of the conclusions drawn from this research can be identified through careful observation of the path diagram in and from Tables (1-4). Starting with the exogenous variable, Household Occupancy, the number of people living in a home has a direct and positive effect on both dwelling Floor Area (β = 0.19**) and HHLD Income (β=0.33**). Household Occupancy also has direct and positive effect on Annual Energy Expenditure (β=0.31**). A similar analysis can be completed for total effects, which is calculated as the sum of direct and indirect effects (Table 6). For example, for each extra person living in a dwelling, the expected mean floor area will increase by 7.27m^2 (β=0.31**), the mean annual household income will increase by £2,463 (β=0.33**), and the mean energy bill will increase by £88/year (β=0.42**). Moreover, by considering the standardised regression weights for total affects it is possible to compare the relative magnitude of effects across different variables. Here, it is shown that Household Occupancy has the largest overall effect on energy expenditure (β= 0.419**) followed by Floor Area (β= 0.258**) and HHLD Income (β= 0.241**). It is important to note however, that Household Occupancy is strongly mediated by both HHLD income (β=0.33**) and Floor Area (β=0.19**). This implies that although the direct effect of Household Occupancy on energy expenditure is just (β=0.31**) when the indirect effect of occupancy through larger floor area and higher household income is allowed for, the total effect of household occupancy increases to (β= 0.419**). Where, β-values can be interpreted as a change of 1 standard deviation in the independent variable corresponds β-std.deviations change in the dependent variable.

Because the units of β are standardised to z-scores, it is possible to derive the relative impact of each independent variable on the dependent variable. For example, it is shown that HHLD Income has a larger relative effect on Floor Area (β=0.38) then it does on Energy Expenditure (β=0.15). In fact, for each additional £1,000 in annual HHLD Income the mean Floor Area increases by 1.18m^2. However because Floor Area and Temperature Difference are both mediating variables between HHLD Income and Energy Expenditure it is necessary to use total effects (Table 6**Error! Reference source not found.**) to calculate the overall effect that HHLD Income will have on Energy Expenditure. For instance, using total effects, a £10,000 increase in annual HHLD Income will lead to an expected average increase in Energy Expenditure of £68/year. On the other hand, if we consider only the direct effects of HHLD Income on Energy Expenditure the average increase in Energy Expenditure is only £41/year. The remaining £27/year difference comes from the mediating effect that HHLD Income has on Energy Expenditure through an increase in Floor Area and an increase in the internal Temperature Difference.

An increase in Energy Pattern, as expected, increases both Temperature Difference and Energy Expenditure. Energy Pattern is an ordered categorical variable ranging between 1 and 5 where 1 represents someone who is never home and rarely uses their heating compared to 5, representing a dwelling where heating is on all the time. The difference in annual Energy Expenditure between these two types of users is, on average £139/year. A correlation between Energy Pattern and Occupancy was identified by the modification indices and found to be significant. Such a correlation indicates the possibility of a shared common variable that explains both Energy Pattern and Occupancy. A logical choice for such a shared common variable is the type of relationship between occupants living in the dwelling. For example, a family consisting of several children where one partner stays at home during the week has a positive effect on both Occupancy and Energy Pattern. On the other hand someone who lives alone with a full time job will have a much smaller effect on both Occupancy and Energy Pattern. It was decided the addition of this variable to the model did not materially add any further insight into residential energy consumption and therefore, for the sake of parsimony, was not added to the model. A summary of real effects on annual energy expenditure are shown in Table 11.

Table 8: Real effects on annual energy expenditure (£1996)

Variable	Effect	Annual HHLD Energy Expenditure
HHLD income	Increase £10,000	£67.80
Number of occupants	each extra person	£88.32
Floor area	Each extra 10m^2	£23.44
Temperature	Each 1°C increase	£2.50
Energy pattern	Living room heated week	£27.70
Energy pattern	Bedroom heated week	£27.70
SAP	30 -> 90 SAP	-£222.00

The EHCS does not contain longitudinal internal temperature measurements. Therefore, internal and external temperature readings taken on the day of the survey were used as proxies for average internal temperature measurements. Due to the fact that temperature readings were only recorded on the day of the survey, it is sensible to treat any relationships related to Temperature Difference with caution as results may lead to spurious conclusions. Large measurement error and therefore weak statistical significance between Temperature Difference and annual Energy Expenditure ($P = 0.088$) as shown in Table 4 is similarly not unusual. For completeness the recorded temperature difference was included as a variable in the final model as it does improve the overall model fit statistics and does lead to additional insight into the contribution of different factors and how they may contribute to final energy consumption. Removing this variable from the analysis had very little effect on all the other variables within the model.

One of the most important findings of this research was the discovery and estimation of a non-recursive relationship between Energy Expenditure and SAP. Standard multiple linear regression methods do not allow the calculation of reciprocal relationships between variables, and therefore it is necessary to use SEM to solve such problems. Only after the non-recursive relationship between SAP and Energy Consumption has been allowed for, can the true effect of SAP on energy consumption be demonstrated. Here, it is shown the effect of SAP on Energy Expenditure has a moderate but statistically significant effect ($\beta = -0.22^{**}$), while Energy Expenditure is also shown to effect SAP ($\beta = 0.23^{**}$). That is, for each standardised unit increase in the SAP rating a subsequent decrease in Energy Expenditure of $\beta = -0.22^{**}$ is expected. Similarly and to put this in context, it is necessary to examine the unstandardised regression weights. Remembering that SAP is on a scale from (0-110), for each unit increase in SAP the average saving in annual Energy Expenditure will be £3.73. For example, if a dwelling with a poor energy efficiency rating with SAP=30, is renovated to, say, SAP=90 the expected annual average saving in energy expenditure will roughly be £222 per annum (£UK1996) *Ceteris Paribus*,

Perhaps what is more interesting is the finding that dwellings with a propensity to consume more energy due to higher occupancy rates, higher household incomes, larger floor areas, increased energy patterns and warmer internal temperatures are more likely to have higher SAP ratings. This therefore suggests that homes with a propensity to consume more energy would, in fact, consume even larger amounts of energy if it were not for the fact that these homes were already relatively more efficient when compared to the rest of the building stock.

6.8 The rebound effect

The rebound effect is a phenomenon known to limit the efficacy of energy efficiency improvements in dwellings (Herring 2006; Sorrell 2007; Madlener & Alcott 2009). In most circumstances, an increase in dwelling efficiency will not result in a commensurate decrease in energy consumption. This is often referred to as 'rebound' or 'take-back' and occurs when a proportion of the energy savings are consumed by additional energy use. This is often explained by an increase in thermal comfort due to the occupant choosing higher internal temperatures. Said differently, the occupant will 'take-back' a fraction of their energy savings and use it to increase their thermal comfort. This analysis supports the premise that a rebound effect may exist. Additionally, this analysis shows the complexity of relationships between variables and suggests there are more factors to consider than a simple rebound effect.

This analysis shows there is indeed a relationship between dwelling efficiency (SAP) and energy demand, and each variable has a direct effect on the other. That is to say, increasing efficiency has a negative effect on energy consumption and therefore drives down energy use, ceteris paribus. On the other hand, homes that consume more energy will, on average be more energy efficient than the average, ceteris paribus. This is a chicken and egg type problem. First, homes that are, on average, more energy efficient have greater energy savings and therefore can afford to spend these savings on increased energy consumption i.e. the rebound effect. On the other hand, homes with a propensity to consume more energy have a greater motivation to make their homes more efficient and therefore this leads to higher SAP rates. It is most likely the real answer will be a combination of both these influencing factors acting concurrently within the residential sector.

6.9 Policy implications and conclusions

In this paper, a structural equation model is used to determine the explanatory power and significance of covariates on residential energy consumption. Using SEM, it is possible to test the structure of relationships and therefore show how direct, indirect and total effects interact and drive residential energy consumption. It is shown the largest determinants for explaining residential energy consumption are the number of occupants living at the dwelling, household income, floor area, household energy patterns, temperature effects, and SAP rating. While the number of occupants living in a dwelling is shown to have the largest magnitude of effect, floor area and household income are also substantial drivers. In addition, we show there is strong mediation between causal variables. For instance, household income and the number of occupants living in a dwelling are both strongly mediated by dwelling floor area. In other words, households occupied by more people or have higher incomes live in larger houses and therefore consume more energy.

Possibly the most important discovery of this research is the finding of a statistically significant reciprocal relationship between SAP and residential energy consumption. This is the first time such a relationship has been empirically identified and may have important consequences for the development of new policy aiming to dramatically cut energy consumption from the residential sector. This finding shows that homes with a propensity to consume more energy already have relatively higher SAP rates and therefore suggests the scope for additional savings through the implementation of energy efficiency technologies may be limited. What is more, this finding implies that homes with a propensity to consume more energy will be more expensive to decarbonise due to the law of diminishing returns. On the other hand, if we focus on homes with a propensity to consume less energy, it can be shown that these homes already have relatively lower SAP rates and are therefore in general less efficient. However, these homes tend to be more poorly heated with lower overall internal temperatures. In addition, improving the energy performance of these homes through the implementation of energy efficiency technologies may contribute to the rebound effect acting to increase the average internal temperature rather than decrease energy consumption. These findings suggest the presence of a residential energy efficiency barrier that must be overcome before any real savings from the residential sector can start to accrue. This result may explain why several Government supported projects in the UK aimed at reducing residential energy consumption have not realised their targets. With this purpose in mind, a dual policy approach may have the most effect. Homes with a propensity to consume more energy should be targeted using behavioural methodologies combined with economic penalties and incentives. On the other hand, homes with a propensity to consume less energy, and therefore lower overall SAP rates should be targeted for whole home efficiency upgrades in order to break through the energy efficiency barrier.

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