

# The elasticity of demand is about occupancy, not prices: building European demand curves based on occupancy elasticity

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## Abstract

The peak congestion of the European grid may create significant impacts on system costs because of the need for higher marginal cost generation, higher cost system balancing and increasing grid reinforcement investment. The use of time of use rates, incentives, real time pricing and other programmes, usually defined as Demand Side Management (DSM), could bring about significant reductions in prices, limit carbon emissions from dirty power plants, and improve the integration of renewable sources of energy.

Unlike previous studies on elasticity of residential electricity demand under flat tariffs, the aim of this study is not to investigate the known relatively inelastic relationship between demand and prices. Rather, the aim is to assess how occupancy levels vary in different European countries. This reflects the reality of demand loads, which are predominantly determined by the timing of human activities (e.g. travelling to work, taking children to school) rather than prices. To this end, two types of occupancy elasticity are estimated: baseline occupancy elasticity and peak occupancy elasticity. These represent the intrinsic elasticity associated with human activities of single residential end-users in 15 European countries.

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This study makes use of occupancy time-series data from the Harmonised European Time Use Survey database to build European occupancy curves; identify peak occupancy periods; draw time use demand curves for video and TV watching activity; and estimate national occupancy elasticity levels of single-occupant households. Findings on occupancy elasticities provide an indication of possible DSM strategies based on occupancy levels and not prices.

## **1. Introduction**

The peak congestion of the European grid may create significant impacts on system costs because of the need for higher marginal cost generation, higher cost system balancing and increasing grid reinforcement investment. The use of time of use rates, incentives, real time pricing and other programmes, usually defined as Demand Side Management (DSM), could bring about significant reductions in prices, limit carbon emission from dirty power plants, and improve integration of renewable (Faraqui, 2005; Strachan and Dowlatabadi, 2002). In order to understand the potential for DSM for the residential sector in Europe, a crucial step is to identify peak demand periods and measuring the occupancy elasticity of such peaks, based on the consumption patterns of residential users throughout the day. Residential demand profiles are highly correlated with timing of occupancy (Capasso et al, 1994). This is because at the time of occupancy users are likely to be involved in activities which imply consumption (appliances, lighting, water heating, etc.). When assessing load profiles, active occupancy data are, along with household size, the most important source of information (Abu-Shark et al, 2005).

This paper explores residential peak demand issues with regards to time of occupancy and different elasticity levels of single residents in Europe. It deploys occupancy time-series data from the Harmonised European Time Use Survey (HETUS) database with the dual purpose of building European residential occupancy curves –hence identifying peak occupancy periods in single-occupant households- and estimating the national occupancy elasticity levels of 15 European countries. Based on two different types of

elasticity, i.e. baseline elasticity and peak elasticity, the paper estimates the occupancy elasticity of loads for single-occupant households. Other studies make use of occupancy time-series data to model residential energy use at the national level. The aim of this paper is to identify residential occupancy peaks and assess national occupancy elasticity levels at the aggregate European level.

The paper introduces the methodological approach for the analysis of time-series occupancy data in relation to timing of use (Section 2). It presents the features of HETUS database in relation to active occupancy of single users (Section 3). It develops European residential occupancy curves for single occupants (Section 4) and time use demand curves for TV and video watching activities (Section 5). It models baseline occupancy elasticity and peak occupancy elasticity levels (Section 6). Findings are presented (Section 7) before discussing issues in relation to single residential occupants in Europe, policy implications and scope of further research (Section 8).

## **2. Methodology**

Large amounts of data are available on the timing of generation, transmission, distribution and supply in Europe (European Commission, 2010; International Energy Agency, 2010). However, limited information exists about the timing of consumption. What is more, no attempt has been made to represent a time of use curve of residential consumption at the European level.

In principle, two approaches might be followed in order to fill this gap. The first approach consists of detecting the consumption of individual households via advanced metering

technologies and hence deriving aggregate consumption at national and European level. At the time of writing this paper, advanced metering technologies had just entered the market and pilot trials had been conducted in various countries for measuring time use performance of residential, commercial and industrial users. The great advantage of this approach is that it is precise because it relies on two-way communication systems to record consumption at different times of the day (Darby, 2010). However, thus far advanced metering devices have been rolled out only in a limited number of countries. In 2010 the only European countries which experienced two digits percentages of smart meters over total electricity meters were Sweden (98%), Italy (93%), Finland (19%) and Denmark (13%) (Torriti et al, 2010). In other countries, e.g. UK, plans have started to install advanced meters in all households by 2021. Europe-wide data are not likely to be available for some time.

A second approach implies deriving the timing of demand for European residential users from available occupancy data. This means capturing the timing of the day when residential users are active occupants, i.e. carrying out activities which involve the use of lighting, heating and household appliances. A similar approach is followed by Richardson et al (2010), who developed a bottom-up occupancy model for UK energy demand starting from the UK Time Use Survey. Their study defines 'active occupants', those users who are in the house and not sleeping. Since additional occupants have a less than marginal impact on household consumption (Mansouri et al, 1996), in our study households with one active occupant are taken as the unit of assessment for occupancy curves. Single-occupant households prevent the problem of identifying the

additional marginal consumption contribution of multiple occupants, an issue which has not been solved in the literature on residential energy consumption (Yao and Steemers, 2005; Wood and Newborough, 2003). TV and video activities, whose actual energy consumption can be derived from HETUS data, are treated separately, as explained in Section 6.

Once the European residential time of occupancy and peak occupancy periods are determined from HETUS data, elasticity levels can be estimated. By and large, the concept of elasticity is used in the DSM literature to measure how the time of loads varies based on different types of signals (e.g. price signals). Price elasticity of demand, for instance, can be calculated with regard to an increase in the intercept of the price schedule, with regard to the consumer's marginal price, or with regard to the price of a specific tariff tier (Reiss, 2005). Based on the third approach, this paper introduces the concept of occupancy elasticity estimates. In the spirit of Kholer and Mitchell (1984), elasticities are applied to flat tariffs.

In other studies, elasticity estimates have been applied to assess the responsiveness of the time of use demand curve to price changes (Baladi et al, 1998; Filippini, 1995). Unlike previous studies on elasticity of residential demand under flat tariffs (Epsey et al, 2004; Halvorsen et al, 2001; Taylor, 1975), the aim of this study is not to investigate the known relatively inelastic relationship between demand and prices. Rather, the aim is to assess how occupancy levels vary in different European countries. This reflects the reality of demand loads, which are predominantly determined by the timing of human

activities (e.g. travelling to work, taking children to school) rather than prices (Devine-Wright, 2002; Devine-Wright et al, 2009; Kasulis et al, 1981; Palmborg, 1986; Pepper et al, 2009). To this end, two types of occupancy elasticity are estimated: baseline occupancy elasticity and peak occupancy elasticity. These represent the intrinsic elasticity associated with human activities of single residential end-users in 15 European countries.

The baseline elasticity in this study can only in part be interpreted as the extent to which end-users react to flat tariffs by changes in occupancy. The fact that prices are flat implies that end-users' changes in occupancy obviously do not depend on prices. Hence baseline occupancy elasticities simply reflect the probability of changes in occupancy during off peak periods. The results can be useful for further work on stochastic modeling for setting incentives for DSM purposes.

Peak occupancy elasticity estimates measures to what extent occupancy varies within peak occupancy periods. Peak occupancy elasticity gives an indication of how elastic loads are at peak occupancy times. Baseline occupancy elasticity and Peak occupancy elasticity are measured separately, as explained in Section 6.

### **3. The Harmonised European Time Use Survey (HETUS) database**

National Time Use Surveys have been carried out since the late 1990s. Most European national statistical institutes undertaking time use surveys follow the EUROSTAT guidelines for harmonising time use data. The Harmonised European Time Use Survey (HETUS) database consists of 220,464 comparable observations across 15 countries.

In national time use surveys, the data collection takes place by means of time diaries covering 24 hours. Since the respondents are asked to fill in diaries for one or two randomly designated days, the results are statistically significant only for aggregate frequencies and not for individual users. When looking at demand, a common feature is share by time use profiles which only become significant at high levels of aggregation (Hobbs and Horn, 1997).

The active occupancy of end-users can be measured indirectly through activities taking place in the household, excluding sleeping. The activities are registered in diaries with intervals of 10 minutes. Most DSM programmes require a level of granularity in time of use data of between 5 and 30 minutes. The 10 minute period is very often considered as the necessary time of use interval for DSM and Demand Response programmes. For example, Demand Response programmes in California making use of ancillary services consist of reductions in the underlying load within periods of 10 minutes. In Finland, synchronised reserve programmes imply that loads can be removed from the system within 10 minutes of the request from the ISO dispatcher thanks to equipment electrically synchronised via smart meters.

In addition, the HETUS database guarantees that the period of the year is heterogeneously distributed. The occupancy data series are associated with all seasons and both weekday and weekend data. Time use energy demand varies significantly depending on seasonality and weekday vis-à-vis weekend sampling (Berry, 1993). Correspondingly, occupancy is also dependent on seasonality and the

weekday/weekend divide. The high level of aggregation of the HETUS database ensures coverage of all periods of the year, including summer and winter, and periods of the week, i.e. both weekdays and weekends.

The HETUS database is coded according to household occupancy. It was consequently possible to extract single-occupant households for this analysis. As previously mentioned, the treatment of single-occupant households data is necessary in order to narrow the gap between occupancy and time use consumption.

#### **4. The European residential occupancy curve for single residents**

The relative occupancy curves for single residents of different European countries is represented in Figure 1. The relative occupancy curves do not take into account population, but simply the percentage of active homes (i.e. percentage of households with one active occupant).

**Figure 1-Relative occupancy curves for single residents in 15 European countries**

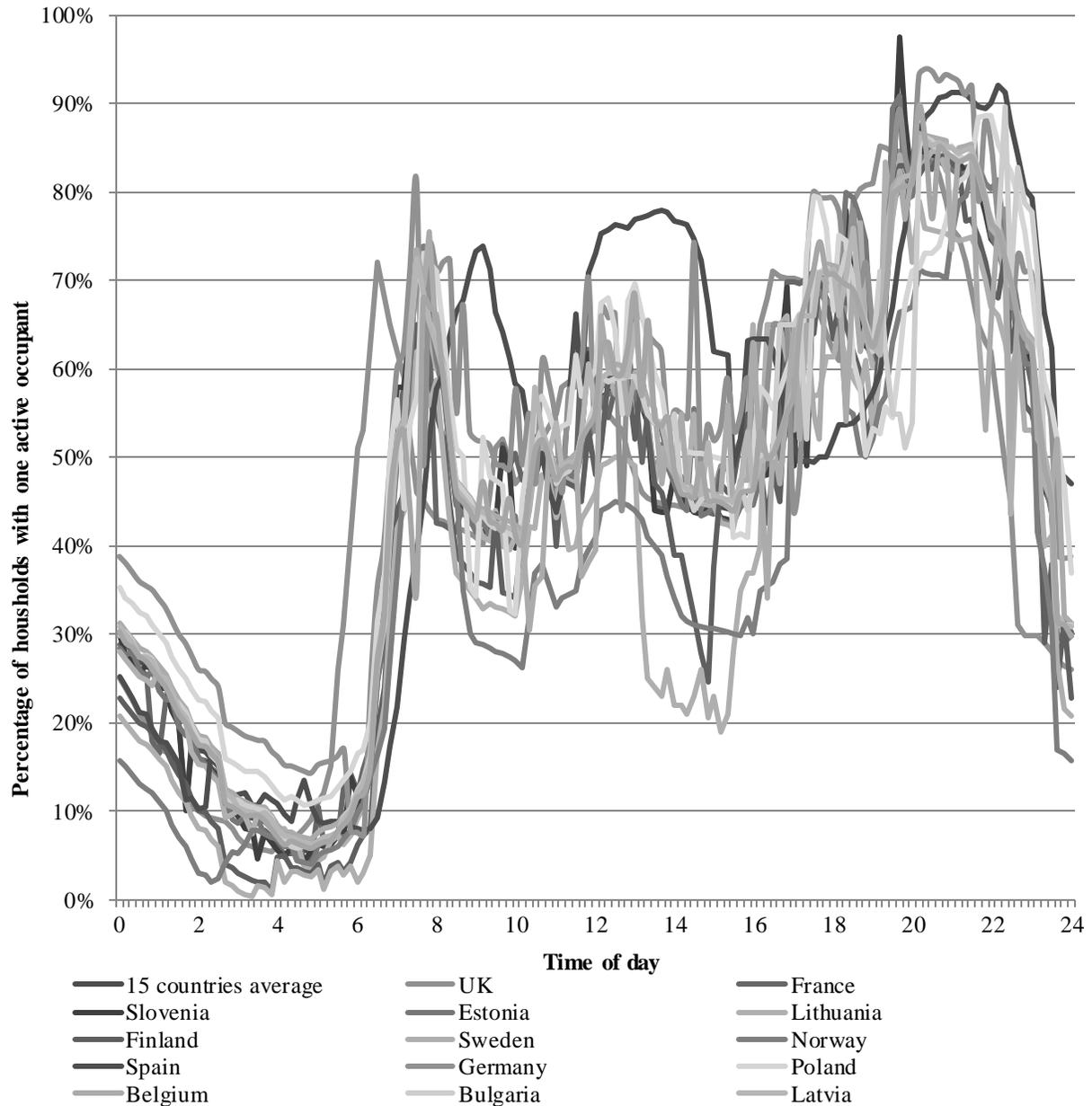
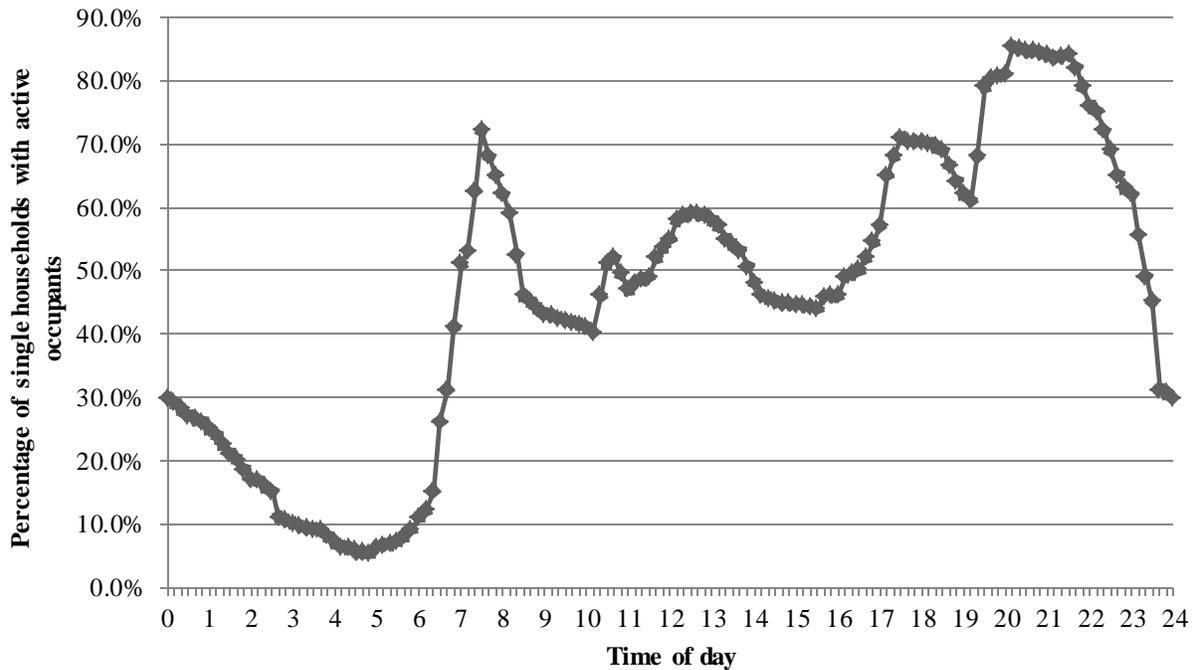


Figure 2 illustrates the percentages of active occupants per countries in our European sample against hours of the day. Relative occupancy by country varies across time. However, the residential occupancy profiles follow similar patterns. The high level of aggregation of the occupancy data permits identifying peak areas between 8h00 and 9h00 and between 19h30 and 20h30.

**Figure 2-Average relative occupancy curve for single residents**



The magnitude of peak occupancies at European level is demonstrated by taking absolute figures on population of households. When calculating absolute residential occupancy figures, the number of households is derived from the European Environment Agency (2001) in correspondence with the year of each country's Time of Use national survey. From Figure 3 it can be observed that the highest percentage of houses with active occupants is between 20h10min and 20h20min.

**Figure 3-Absolute occupancy curves for single residents in 15 European countries**

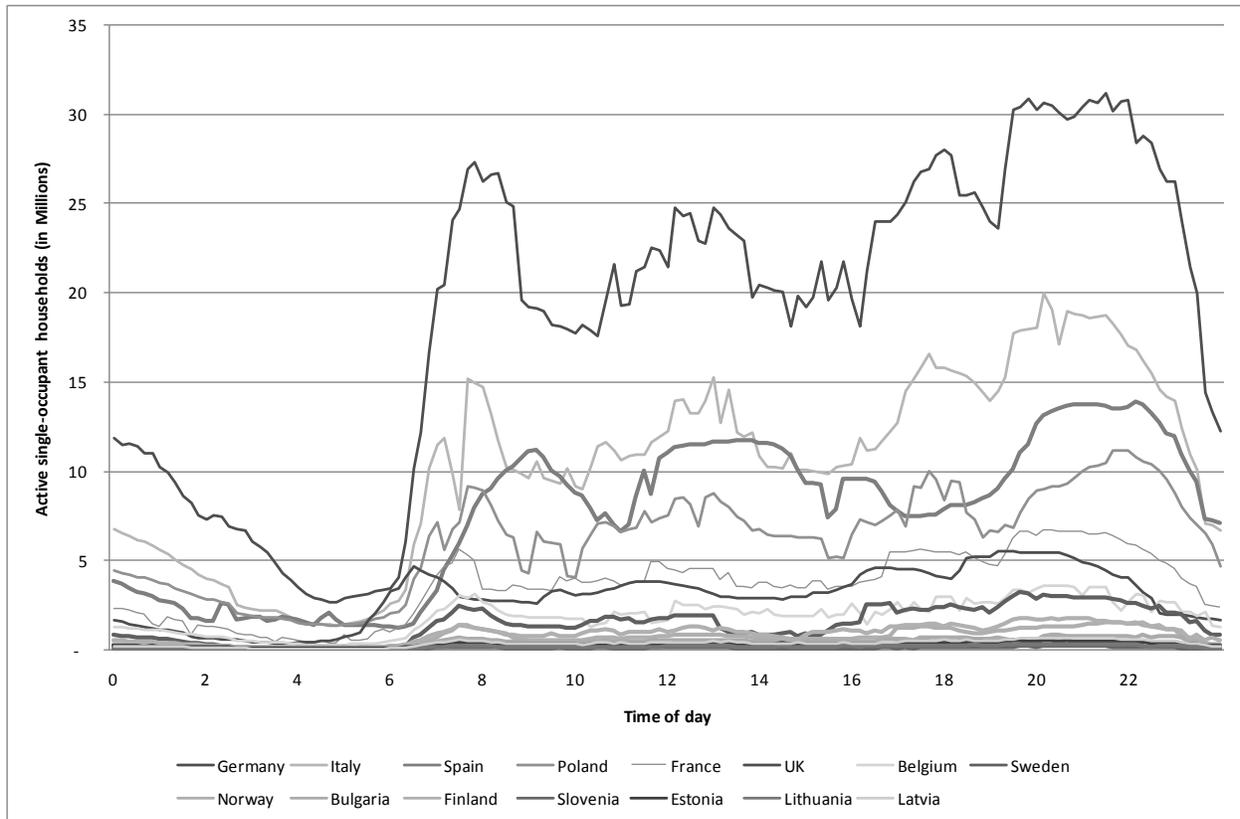


Figure 3 shows absolute occupancy levels. The occupancy curves present extremely low levels of active occupancy during night hours, very high levels of active occupancy during meal periods for Central European Time CET. Figure 3 combines HETUS data on active single residential households with average figures of single households for the period between 1992 and 2009, when time use surveys on which the HETUS data is based were carried out. It can be noted the weight of single residents in Germany, Italy and Spain.

Table 1 shows activities at 20h20min in various countries from the HETUS survey. At the time of highest active occupancy, in countries like Lithuania, Latvia, Norway active

occupants are mainly spending free-time. In Italy, France and Bulgaria active occupants are generally eating. In the majority of countries, excluding Italy and Spain a vast number of active occupants is involved in TV and video activities.

**Table 1-Activities at 20h20min in 15 European countries**

Country	Start Time	Work and study	Travel to/from	Household work	Sleep and other	Eating	Free time	TV and video	Unspecified time
Belgium	20:20	4.5	0.63	15.37	4.58	13.72	22.1	36.76	2.35
Bulgaria	20:20	3.66	0.75	16.08	3.75	26.53	10.11	38.84	0.28
Finland	20:20	6.86	0.62	16.87	7.4	6.95	26.76	32.52	2.02
France	20:20	4.49	1.05	15.88	4.29	36.71	10.34	24.58	2.65
Estonia	20:20	7.08	1.55	19.86	5.56	9.29	20.08	35.86	0.73
Germany	20:20	4.49	0.79	12.32	3.22	9.83	29.63	38.58	1.14
Italy	20:20	4.1	1.44	18.45	4.18	38.97	16.46	15.06	1.34
Latvia	20:20	8.18	2.25	15.12	4.94	13.16	16.22	39.63	0.51
Lithuania	20:20	7.76	1.13	17.2	6.91	11.45	13.96	40.9	0.68
Norway	20:20	6.89	0.61	18.86	2.61	7.86	39.08	23.69	0.38
Spain	20:20	11.37	2.66	25.03	4.92	8.68	34.16	12.72	0.46
Poland	20:20	6.22	0.81	15.48	7.99	10.54	17.38	40.74	0.86
Sweden	20:20	6.88	0.65	16.69	3.29	8.8	29.22	33.58	0.89
Slovenia	20:20	6.34	0.75	15.08	8.48	8.85	21.07	39.08	0.35
UK	20:20	5.68	0.9	15.18	4.2	9.16	26.44	37.29	1.15

## 5. From European residential occupancy curve to time use demand curve: TV and video watching activities

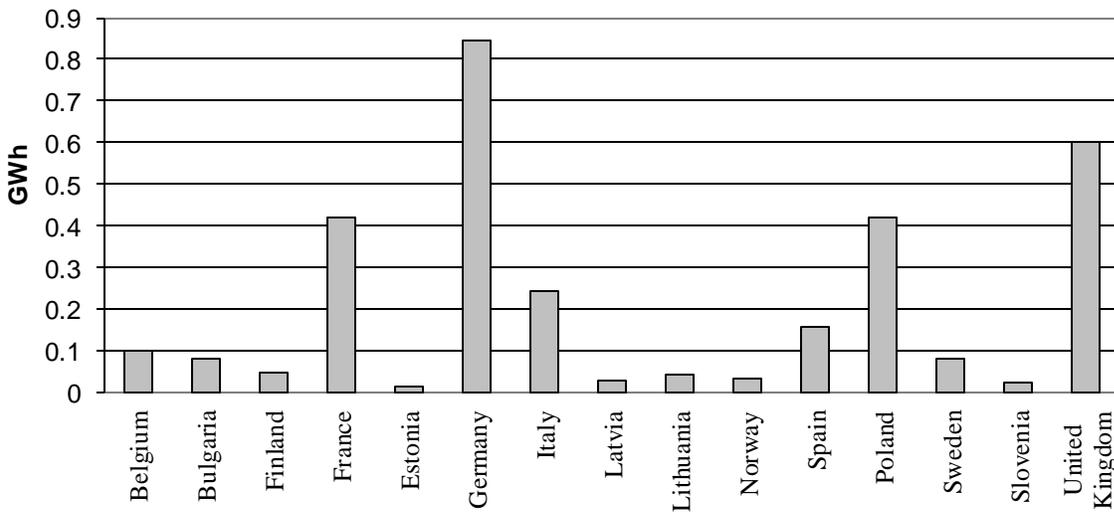
Since HETUS data specify the amount of time spent on watching TV and video activities, it is possible to reconcile the time spent at a given time on these activities with electricity consumption. The average electricity consumption of European TV and video devices is taken from Smart-A data (Smat-A, 2009). Using data on active occupancy, levels of occupancy per household, average European consumption for TV and video devices,

and average TV and video population (per country), it is possible to model linearly the time use demand curve for TV and video activities as follow. For a single country  $i$ , time use demand for TV/video activities at the time  $j$  is

$$D_{i,j} = (O_{i,j} \times T_i) \times K$$

where  $O_{i,j}$  is the total active occupancy of houses with occupant involved in watching TV/video at time  $j$ ;  $K$  is a parameter representing average European consumption for TV and video devices; and  $T_i$  is the average TV and video population in that country  $i$  for single households. The results are shown in Figure 4, which illustrates the size in GWh of peak load for this activity at 20h20.

**Figure 4-Contribution of TV/video watching activities at 20:20**



The contribution to European peak electricity load of the activity of watching TV and video at 20h20 is up to 3.1 GWh, the equivalent of the year generation from onshore wind in the UK in 2008 (DECC, 2009).

## 6. Modelling occupancy elasticity

Variations in occupancy profiles provide the basis for occupancy elasticity estimates. Changes in occupancy from a 10 minute interval to the next 10 minute interval are measured for the period  $i$  and the country  $j$  as

$$\Delta (t, t + 1) = \omega_{t+1} - \omega_t$$

where  $\omega_t$  is the level of occupancy at the time  $t$ . The Delta occupancy level measures variations between time intervals. High Delta occupancy levels indicate a high variation in occupancy patterns between two time periods. The cumulative occupancy variation is determined as the variation in occupancy levels across periods

$$\rho = \sum |(\omega_{t+1} - \omega_t)|$$

The cumulative occupancy variation provides absolute variations across 10 minute intervals. It allows comparison of countries' occupancy data in terms of absolute variations in the occupancy curve. Countries with a high  $\rho$  are associated with higher probabilities of changes in occupancy between 10 minute periods.

The baseline elasticity of each country is derived as ratio of the change in the occupancy variable to the percent change from a 10 minute interval to the next 10 minute interval. The baseline elasticity relates an interval to the level of occupancy in the following interval.

$$\beta_{t,t+1} = \frac{\partial \omega_t}{\partial \pi_{t+1}} \frac{\pi_{t+1}}{\omega_t}$$

where  $\pi_{t+1}$  is the retail price at the time  $t+1$ . In relation to energy consumption, price is used in all elasticity studies, even where flat rates are the only price option offered by suppliers (Terza and Welch, 1982).

The peak elasticity coefficient is determined as the changes in the occupancy function at peak occupancy times from 10 minute intervals to the next 10 minutes. Peak elasticity provides an indication of how elastic loads are at peak occupancy time, because it measures how much occupancy varies within peak occupancy periods. Peak elasticity can be interpreted as how likely it is that occupancy will vary within peak periods. In other words, high elasticity during peak periods means that it is more likely that at peak time there are changes (reductions) in occupancy which will enable shifts in loads.

In order to determine peak elasticity, the elasticity for the two intervals  $t$  and  $t+1$  is adapted from Kohler and Mitchell (1984) as

$$\mu_{T,T+1} = \frac{\partial (\omega_T/\omega_{T+1})}{\partial (\pi_T/\pi_{T+1})} \frac{\pi_T/\pi_{T+1}}{\omega_T/\omega_{T+1}}$$

Where  $\omega_T$  is the level of occupancy at the peak time  $T$ . The elastic period for each country is limited to 80 minutes per day, i.e. 40 minutes for each of the two main peak events, so that  $T \in (1,4)$ .

Under the assumption of flat retail tariffs ( $\Pi_t$ ) in all 15 countries, baseline elasticity can be re-written as:

$$\beta_{t,t+1} = \frac{\partial \omega_t}{\partial \Pi_{t+1}} \frac{\Pi_{t+1}}{\omega_t}$$

Following replacement of flat rates and applying chain rule, peak elasticity is re-written as

$$\mu_{T,T+1} = \frac{(\omega_T/\omega_{T+1})}{(\Pi_T/\Pi_{T+1})} \left[ \frac{1}{\omega_{T+1}} \frac{\partial \omega_T}{\partial \Pi_{T+1}} \frac{\partial \Pi_T}{\partial (\Pi_T/\Pi_{T+1})} - \frac{\omega_T}{(\omega_{T+1})^2} \frac{\partial \omega_T}{\partial \Pi_T} \frac{\partial \Pi_T}{\partial (\Pi_T/\Pi_{T+1})} \right]$$

Data for flat retail tariffs are obtained from Eurobarometer (2010) for the same years where the national Time Use surveys were conducted.

It should be noted that peak periods take place twice during each 24 hours. This means that peak elasticity is contained within baseline elasticity. Hence, the difference between baseline elasticity and peak elasticity gives the elasticity of loads at off peak times.

A country with an elastic occupancy load for single occupants is associated with high variability in loads throughout the day. This means that DSM programs can rely on existing changes in consumption which are intrinsically triggered by changes in occupancy. Correspondingly, a country with an inelastic occupancy load for single occupants is associated with a lower peakiness.

## **7. Elasticity results**

The occupancy elasticity levels of individual countries provide a basis for DSM activities in Europe at the residential level. The changes in occupancy determine the intrinsic elasticity of loads in the 15 sample countries. Peak elasticity determines to what extent consumers in one given country are capable of shifting loads during peak consumption time.

Baseline elasticity estimates are determined using a bottom-up approach from all time intervals. Table 2 illustrates the baseline elasticity estimates for the period between 16:00 and 17:00 in Belgium, Bulgaria, Finland and Estonia. The number of observations refers to the number of single households per country, as identified in the HETUS database.

**Table 2-Baseline elasticities for the period between 16:00 and 17:00 (standard errors in parentheses)**

Period of the day	Belgium	Bulgaria	Finland	Estonia
$\beta_{16.00}$	0.142 (0.014)	0.092 (0.012)	0.102 (0.008)	0.136 (0.009)
$\beta_{16.1\bar{6}}$	0.146 (0.026)	-0.025 (0.018)	0.014 (0.028)	0.044 (0.015)
$\beta_{16.\bar{3}}$	0.090 (0.033)	-0.025 (0.026)	0.031 (0.019)	0.020 (0.020)
$\beta_{16.50}$	0.089 (0.020)	-0.004 (0.016)	-0.007 (0.014)	0.003 (0.016)
$\beta_{16.\bar{6}}$	0.057 (0.028)	0.018 (0.017)	0.019 (0.015)	0.012 (0.017)
$\beta_{16.8\bar{3}}$	0.194 (0.043)	-0.033 (0.023)	0.057 (0.012)	0.057 (0.023)
Observations	2651	2740	1998	1654

National baseline elasticity levels are averaged for the 24 hours of the day. Peak elasticity estimates are determined for 80 minutes per day, i.e. 40 minutes for each of the two main peak events. To the morning peak, which according to Figure 2 takes place at 7:30, corresponds peak elasticity  $\mu_{MP}$ . The evening peak at 20:20 is associated with peak elasticity  $\mu_{EP}$ .

Non-peak elasticity levels are estimated for elasticities of non-peak periods by excluding both peak periods, i.e.  $\beta - \mu_{MP}$  and  $\beta - \mu_{EP}$ . The non-peak elasticities become useful when considering the ‘most value’ tests of DSM programs (Hobbs, 1991).

The ratio between peak elasticity and baseline elasticity determines the intrinsic elasticity of single households. In other words, the ratio quantifies how great the occupancy elasticity is between on-peak and off-peak consumption.

With regards to the standard errors in parenthesis in both Table 2 and Table 3, this should be interpreted as precision of the estimation of the elasticity. Hence, the higher the variance associated with the elasticity estimate, the less weight it is given in the calculation of the common mean and the more it will shrink to the common mean.

If the intrinsic elasticity in the equation for Finland has a lower standard error than for Belgium, the common mean should be closer to the 'Finnish' elasticity. If the estimate of the elasticity varies more across the different countries than the elasticity of employment-hours to wages, then the first will be shrunk by more than the latter.

**Table 3-Baseline elasticities, peak elasticities and non-peak elasticities by country (standard errors in parentheses)**

Country	$\beta$	$\mu_{MP}$ $\mu_{EP}$	$(\beta - \mu_{MP})$ $(\beta - \mu_{EP})$
Belgium	0.193 (0.027)	0.051 0.034	0.142 0.159
Bulgaria	0.194 (0.071)	0.048 0.011	0.146 0.183
Finland	0.130 (0.056)	0.024 0.010	0.106 0.120
Estonia	0.127 (0.028)	0.008 0.021	0.119 0.106
Germany	0.113 (0.015)	0.043 0.022	0.070 0.091
Italy	0.124 (0.023)	0.049 0.024	0.075 0.100
Latvia	0.128 (0.027)	0.011 0.024	0.117 0.104
Lithuania	0.131 (0.025)	0.009 0.018	0.122 0.113
Norway	0.130 (0.026)	0.057 0.012	0.073 0.118
Spain	0.192 (0.031)	0.064 0.057	0.128 0.135
Poland	0.101 (0.019)	0.051 0.012	0.060 0.089
Sweden	0.126 (0.025)	0.054 0.014	0.072 0.112
Slovenia	0.144 (0.023)	0.041 0.025	0.103 0.119
United Kingdom	0.165 (0.023)	0.091 0.020	0.074 0.145

This analysis on baseline elasticities, peak elasticities and non-peak elasticities by country provides an indication of possible DSM strategies based on occupancy levels. Countries with characterised by high peak elasticity levels, like, for instance Belgium ( $\mu_{MP} = 0.051$  and  $\mu_{EP} = 0.034$ ) and Spain ( $\mu_{MP} = 0.064$  and  $\mu_{EP} = 0.057$ ) might be a field of experiment for smart appliances, which can be remotely activated when single residents are not in the household during a peak event. In countries with low peak elasticity, like Estonia ( $\mu_{MP} = 0.081$  and  $\mu_{EP} = 0.021$ ) and Lithuania ( $\mu_{MP} = 0.009$  and  $\mu_{EP} = 0.018$ ), manual and incentive-based DSM programmes might be applied. These normally consist of occupants receiving peak signals through smart meters and being rewarded (or penalised) based on their response to peak signals. The reason why manual and incentive-based DSM programmes might work with low peak occupancy elasticity is because they require high occupancy during peak events. In cases where non-peak elasticity is low, e.g. Germany ( $\beta - \mu_{MP} = 0.07$  and  $\beta - \mu_{EP} = 0.091$ ), discrete demand control algorithms which pre-determine the levels of consumption for specific residential demand services. In cases of high baseline elasticity, e.g. Belgium ( $\beta = 0.193$ ), Bulgaria ( $\beta = 0.194$ ), Spain ( $\beta = 0.192$ ) and UK ( $\beta = 0.165$ ), Time of Use programmes might be a palatable form of DSM, for individual occupants who plan to carry out activities within pre-set off peak periods.

Three more observations can be drawn from Table 3. First, in every country baseline occupancy elasticity levels are lower than peak elasticity levels. This reflects the fact that during peak periods a higher number of single residents remains in the household. Second, in cases like Bulgaria, where to a high baseline elasticity does not correspond high peak elasticity, single residents leave and return to the household frequently

throughout the day except for peak times. Third, the UK features high peak elasticity during the morning peak and low peak elasticity during the evening peak. This is partly attributable to time difference.

## **8. Conclusions**

The results of this paper on occupancy elasticity apply to single households only. As mentioned in Section 3, this prevents problems of modeling consumption by additional end users. The relatively small increases in population in the EU area coupled with more significant increases in household numbers since the 1990s mean that the average household size has been decreasing and is destined to decrease further in the future (Boardman, 2007). In the European area, the average number of persons per household decreased from over 2.8 in 1980 to about 2.4 in 1998 (European Environment Agency, 2001). The consequences of such decreases of house sizes of European households are beyond the remit of this paper. However, it is noted that compared with large households, small households are associated with higher energy consumption per capita. Single-occupant households represent more than one third of all the households in Europe. This share is projected to increase to 36% by 2015 (OECD, 1998). Besides considerations about the demographics of single households, in the future the integration of renewable heat technologies, such as air source heat pumps, combined with electric vehicles might lead to enhanced peak requirements.

In this paper occupancy was used as a proxy for time of use demand. However, the intensity of consumption of occupants is not given by occupancy only. Just to provide two examples, lighting consumption depends on natural light; white goods consumption

is related to the energy efficiency of individual appliances; cooling and heating electric systems are dependent on temperature. Other studies have modelled the impacts of natural lighting on artificial lighting (Richardson et al, 2009; Papagiannis et al, 2009). Indeed these could be modelled by researchers interested in 'closing the gap' between occupancy curves and timing of demand.

While the large sample (220,464 observations) and harmonisation of the HETUS data set is reassuring with regards to the statistical significance in terms of occupancy data, the correlation with time of energy use can only be validated upon cross-comparison with real time of consumption data from smart metering applications. As noted in Section 2, this is not possible until large smart meter roll-out projects have taken place in various European countries. For the time being, it is worthwhile noting that the occupancy profile of an aggregate European grid demonstrates significant similarities to smaller domestic electricity demand profiles (Elexon, 2007).

A separate consideration regards time zones. If Europe operated as a single grid, peak demand would be partly mitigated by different time zones. This paper took into account the different time zones of the 15 countries. This means that the timing of consumption of countries like UK, Bulgaria, Lithuania and Latvia were adjusted to CET. For instance, time use survey data at 18h00 (Greenwich Meridian Time) in UK is shifted to 19h00 (Central European Time). Previous studies examined the impacts of shifting countries like the UK to Central European Time by focusing on the ameliorative aspects of peak time savings (Hill et al, 2010). Should a central European grid come to place, positive

impacts would be mitigated by the negative impacts of peak increments in the European grid.

It has been observed that European DSM programmes have been largely neglected compared with e.g. energy efficiency and renewable policies (Pollitt, 2008; Strbac, 2008). The importance of assessing occupancy peaks in relation to residential load profiles is destined to increase. The highly electric low carbon future envisaged in most European energy and climate change policies (Anderson et al, 2008) implies that large portions of energy demand will largely be supplied by electricity, with peak demand increases disproportionately higher than absolute energy demand increases. Other research has identified high penetration of electric vehicles (Bonilla and Foxon, 2009) and renewable sources of heat (Speirs et al, 2010) as incremental factors to peak demand. This will add considerably to the peaks in electricity demand unless DSM is implemented to shift these peaks to lower-demand times in the diurnal cycle. For instance, air source heat pumps will add significantly to peak electricity demand because manufacturers typically install direct electric resistive backup heating in devices. According to the UK National Grid, peak demand in Britain is currently around 60GW. With air source heat pumps, peak demand in Britain is likely to increase by tens of GW. This is because the peak demand of a domestic air source heat pump will be around 7kW in winter conditions. The aggregate effect of heat pumps may be around 1.3kW per home (Strbac et al, 2010).

In the 'all electric' low-carbon future, DSM is destined play a more important role than it is playing at the moment in most European countries. For instance, in the UK at the

moment the only two significant DSM programs are –Time of Use (Economy 7 and Economy 10) for residential users and Interruptible Programs for large industrial users. These programs cover a minority of electricity consumers in the UK.

The identification and management of peaks in residential consumption will be a fundamental aspect for reducing low system costs and balancing supply and demand. The profile of aggregate energy use curves is a preliminary assessment of the potential of DSM programmes, tariff system, or incentive policy. This paper makes a preliminary step towards Europe-wide time use demand curves by building European residential occupancy curves, identifying peak occupancy periods in single-occupant households, and estimating the national occupancy elasticity levels of different European countries. In addition, European time use demand curves were derived for TV and video watching activities.

Most of the European markets examined in this paper are not fully liberalized, meaning that at national level DSM activities are not driven by end-users time of consumption of energy. Under the assumption that markets are liberalized, also following the EU directive on liberalization of energy markets (Newbery, 2002; Green et al 2009), the fragmentation of the market should take place based on actual time of consumption.

The extent to which peak loads might be shifted is largely dependent on the elasticity of occupancy levels. The interpretation of the results on elasticity of occupancy could be connected with different typologies of DSM activities. For instance, in cases where variations in occupancy during peak periods are very high (high peak elasticity),

automated DSM programmes, where appliances can be remotely operated may be more suitable for shifting loads. In cases where variations in occupancy are very low during peak periods (low peak elasticity), manual, incentive-based forms of DSM, where occupants receive peak signals through smart meters and are rewarded (or penalised) based on their response might be more applicable (Torriti and Leach, 2011). In cases where baseline elasticity is low, it might be possible to have discrete demand control algorithms which determine, for instance, the levels of consumption for heating services. In cases of high baseline elasticity, Time of Use programmes might be the most adequate form of DSM.

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