Estimating income and price elasticities of residential electricity demand with Autometrics*

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Abstract

This paper estimates the income and price elasticities of the residential electricity demand for twelve major European countries using annual time series from 1975 to 2018. In the modelling exercise we adopt a novel econometric approach that features automatic model selection, saturation methods for detecting outliers and structural breaks, and the automatic model selection algorithm Autometrics. The selected specification for each country is an error correction model, from which it emerges a cointegrating relationship between electricity consumption, income, electricity price and climate variables, once that outliers and breaks are accounted for. The empirical results show that the estimated long-run income elasticities are less than one for all countries, and that the long-run price elasticities are in all cases less than one in absolute value. These results suggest that for European countries electricity is a normal good and that demand is price inelastic.

Keywords: Electricity demand modelling, income and price elasticities, automatic model selection, saturation methods, Autometrics.

JEL Classification Numbers: C22, Q41.

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1 Introduction

The goal of the European Union (EU) is to provide secure, sustainable, competitive and affordable energy to households and businesses (European Commission, 2015). To this aim the EU has enacted several legislative acts to improve energy efficiency at all stages of the energy supply chain, increase the share of renewable energy sources in the energy mix, and support low-carbon technologies. Energy legislation has also introduced a new design for the electricity market that allows electricity to move across the EU countries and attracts investment in energy storage.

Accurate estimation of income and price elasticities of electricity demand is of great importance to design effective energy and environmental policies and to assess the related welfare changes (Schulte and Heindl, 2017). There is a huge body of literature that has been produced on the topic over the last decades, see among others Silk and Joutz (1997), Beenstock et al.(1999), Filippini and Pachauri (2004), Hondroyiannis (2004), Narayan et al.(2007), Amarawickrama and Hunt (2008), Dergiades and Tsoulfidis (2008), Nakajima and Hamori (2010), Alberini et al.(2011), Bernard et al.(2011), Dilaver and Hunt (2011a,b), Blázquez et al.(2013), Krishnamurthy and Kriström (2015), Csereklyei (2020).

The majority of previous empirical studies have used aggregate macro data at country or subnational/state level, whereas a comparatively smaller number of papers has used household survey data. The quantitative methods most adopted include various types of time series cointegration models, structural time series models (STSM), and panel data methods. The control variables also differ across the studies, but typically include a measure of income, electricity price, price of substitute products, climate indexes, population, degree of urbanization and, for studies using household survey data, households characteristics (e.g. size, age of the components, level of education) and several dwelling features. A few papers (inter alia Amarawickrama and Hunt, 2008; Dilaver and Hunt, 2011a,b; Atalla and Hunt, 2016) control for energy efficiency improvements and other exogenous factors such as changes in tastes, behaviour and regulation. Their approach is to estimate a STSM for the electricity demand, where the above factors are unobserved and are modelled with a stochastic trend, named the Underlying Energy Demand Trend (UEDT), that features outliers and structural breaks. This methodology addresses the issue of modelling outliers and breaks only partially, as it does not permit to test for all possible outliers and breaks that may have occurred over the estimation period. Overall, with the exception of scholars using the STSM approach, the modelling of outliers and structural breaks has received only little attention in the literature on estimating income and price elasticities of electricity demand, as opposite to what has happened in the literature on time-series forecasting (see among others Arora and Taylor, 2013). Hence the need to investigate this matter further.

This paper offers a contribution to fill this gap in the literature on estimating income and price elasticities of electricity demand in that it adopts a novel econometric approach to detect for outliers and structural breaks. The approach is to use automatic model selection, saturation methods to model outliers and structural breaks (see inter alia Hendry, 1999; Santos et al., 2008; Johansen and Nielsen, 2009; Castle et al., 2011; Castle et al., 2012 Castle et al., 2015, Hendry and Doornik, 2014, Bergamelli and Urga, 2016 and Ericsson, 2017) and the search algorithm Autometrics (Doornik, 2009 and Doornik and Hendry, 2018). In particular, we specify a general unrestricted error correction model for residential electricity demand using annual time-series aggregate data on electricity consumption, income, price and climate variables, which we saturate with T (=number of observations) Impulse and T Step Indicator dummies that capture outliers and structural breaks. Estimation is performed with the search algorithm Autometrics, which allows to conduct automatic model selection when there are more variables than observations, as is our case. With this approach we obtain consistent estimates of income and price elasticities, since the automatic model selection gives a congruent, that is robust to mis-specification, and parsimonious model.

The empirical exercise is conducted for twelve major European countries, namely Austria, Belgium, Denmark, France, Germany, Ireland, Italy, Spain, Portugal, Sweden, the Netherlands and the UK, using annual time series for the period 1975-2018. In 2018, the residential sector of these countries accounted for about the 82% of the total EU-28 residential consumption. To the best of our knowledge this is the first study that uses this econometric approach to estimate income and price elasticities of electricity demand.

The empirical results show that the estimated long-run income elasticities are less than one for all countries, and that the long-run price elasticities are in all cases less than one in absolute value. These results confirm the findings that electricity is a normal good for European countries and that demand is price inelastic. At the same time, the results show differences in the estimated elasticities across countries, which can be attributed to differences in per-capita GDP and in energy efficiency levels attained.

The remainder of this paper is organized as follows. Section 2 provides a short review of the most relevant literature on residential electricity demand modelling. Section 3 presents the dataset employed in the analysis and describes the econometric methodology adopted, while estimation results are reported and discussed in Section 4. Section 5 concludes.

2 Literature

Forecasting future needs of electricity and understanding the responsiveness of electricity demand to changes in its main drivers income and price are of great importance for both the power industry and the policy makers. The power industry is especially interested in determining the optimal operations and investment planning of electricity generation and distribution. Policy makers are most concerned with the design of energy and environmental policies that allow to achieve secure, sustainable and affordable supplies (European Commission, 2015).

In the past decades, a large number of academic and policy papers have been published on both the estimation of income and price elasticities and the forecasting of electricity. Scholars have proposed alternative methods for estimating and forecasting electricity demand (often referred to as load) for different time horizons. These latter are typically grouped into four categories (see Weron, 2006 and Hong and Fan, 2016): (a) very short-term load forecasting, which considers the interval from minutes to one hour ahead and is applicable to real-time load control; (b) short-term load forecasting, where load is sampled at daily basis and the forecast serves for scheduling the generators and operating the transmission system;(c) medium-term forecasting, which ranges from one week to one year ahead and is used for forecasting fuel needs and maintenance of the system elements; (d) long-term forecasting, where the horizon is several years ahead and the purpose is the strategic planning of the power system and the design of energy policy. Weron (2006) provides an overview of the most used modelling and forecasting methods, which include statistical techniques (namely multiple linear regression, semi-parametric additive models, autoregressive moving average models and exponential smoothing models) and artificial intelligence techniques (namely artificial neural networks, fuzzy regression models, support vector machines and gradient boosting). Hong et al. (2020) provide a review of the literature on load forecasting and illustrate some of the emerging lines of research. In particular, they discuss the use of machine learning and artificial intelligence techniques, forecast combinations, hierarchical forecasting and probabilistic load forecasting. The last two methods are those where the literature is most limited at present. Hong and Fan (2016) provides a review of the literature on probabilistic load forecasting, whereas Taieb et al. (2021) is one of most recent contribution on hierarchical probabilistic forecasting using UK residential smart meter data.

This paper adds to the strand of literature on statistical modelling of residential electricity demand. In particular, our empirical exercise aims to estimate income and price elasticities that can help designing energy and environmental policies for European countries. Given the aim of the paper, in what follows we focus only on reviewing the most recent literature on the estimation of income and price elasticities for residential electricity demand. These studies can be divided in two broad groups: the first, and largest one, using aggregate data on electricity consumption, income, price and various other factors such as price of substitute products, climate indexes, housing stock, population and degree of urbanization; the second one, more limited, using micro data from surveys on household features, dwellings characteristics and use of appliances. To the first group of studies belong, among others, Silk and Joutz (1997), Beenstock et al.(1999), Filippini (1999), Fatai et al.(2003), Holtedahl and Joutz (2004), Hondroyiannis (2004), Narayan and Smyth (2005), Halicioglu (2007), Narayan et al. (2007), Dergiades and Tsoulfidis (2008), Amarawickrama and Hunt (2008), Eskeland and Mideksa (2010), Nakajima and Hamori (2010), Alberini and

Filippini (2011), Azevedo et al. (2011), Dilaver and Hunt (2011a, b), Filippini (2011), Jamil and Ahmad (2011), Blázquez et al. (2013), Atalla and Hunt (2016), Cialani and Mortazavi (2018), Filippini et al.(2018) and Csereklyei (2020). In the second group we find, among others, Filippini and Pachauri (2004), Bernard et al. (2011), Krishnamurthy and Kriström (2015), Miller and Alberini (2016), Schulte and Heindl (2017).

In the 1990s and in the first decade of the 2000s, nonstationary time series models were the most used methods to estimate electricity demand, due to the popularity of cointegration analysis in econometrics. Beenstock et al. (1999), Fatai et al. (2003) and Amarawickrama and Hunt (2008) estimate electricity demand using the two-step Engle and Granger method (Engle and Granger, 1987). Silk and Joutz (1997), Beenstock et al.(1999), Fatai et al. (2003), Hondroyiannis (2004), Holtedahl and Joutz (2004), Amarawickrama and Hunt (2008) and Jamil and Ahmad (2011) employ the maximum likelihood estimation approach to multivariate cointegration analysis developed by Johansen (1988). Fatai et al. (2003), Narayan and Smyth (2005), Halicioglu (2007), Amarawickrama and Hunt (2008), and Dergiades and Tsoulfidis (2008) adopt the autoregressive distributed lag (ARDL) bounds testing approach to cointegration developed by Pesaran and Shin (1999) and Pesaran et al. (2001). Cointegration methods allow to obtain short- and long-run elasticities estimates that are optimal as long as no outliers and structural breaks are present. But when this is not the case, the econometric analysis may be affected by the well known omitted variable problems.

The modelling and forecasting of outliers in electricity demand have been addressed only by time-series forecasting studies, see among others Arora and Taylor(2013) for an example with high-frequency data, and by the literature using STSM (see among others Amarawickrama and Hunt 2008, Dilaver and Hunt 2011a, b, Atalla and Hunt 2016). The STSM approach, originally by Harvey (1989), involves decomposing a time series into several unobserved components (i.e. trend, seasonality, cycle, irregular) and estimating each component separately. A STSM can then be transformed into a behavioural model by adding exogenous variables, such as income and price if one wants to estimate the related elasticities. The main drawback of these studies is that they do not test for all possible T outliers and T breaks that may have occurred over the period of observation. This in fact is feasible only by using an automatic model selection algorithm that allows to estimate a model when there are more variables than observations, but none of the studies above implements such an algorithm.

More recently, panel data methods have started to be used extensively. Filippini (1999), Eskeland and Mideksa (2010), Azevedo et al. (2011), Bernard et al.(2011) and Miller and Alberini (2016) use static panel data models. Filippini (2011), Alberini and Filippini (2011), Blázquez et al. (2013), Cialani and Mortazavi (2018), Filippini et al. (2018) and Csereklyei (2020) use dynamic panel data models. Narayan et al. (2007) and Nakajima and Hamori (2010) adopt panel cointegration analysis. The main limitation of panel data studies is that they neglect outliers and structural breaks, which is not a surprise given the existing limited theoretical framework for the identification of structural breaks in panel data.

Table 1 provides a summary of the most recent literature that uses aggregate data together with the estimates of the long- and short-run income and price elasticities of residential electricity demand. Income and prices elasticities vary significantly across the studies. Short-run income elasticities range between 0.1 to 1.96, while short-run price elasticities vary between -0.84 and -0.04. Long-run income elasticity is estimated to vary between 0.25 to 1.97, while long-run price elasticity between -2.27 to -0.02. As pointed out by meta-analysis studies (see among others Espey and Espey, 2004 and Labandeira et al., 2017) differences in estimated elasticities may be due to several factors, including the specification of the demand model and the estimation method, the type of data (i.e. time series versus cross-section or panel data), the type of consumer, the country and the sample period and the outlet where the paper has been published. In particular, Labandeira et al. (2017) show that price elasticities from panel data studies are significantly larger that those from time-series ones and that elasticities are smaller for studies using data subsequent to energy crises (i.e. 1973, 1979 and 2008). Fouquet (2014) in a study on trends in income and price elasticities of energy demand in the United Kingdom between the early 19th and the early 21st centuries shows that the absolute values of both elasticities have declined over time, and by implication, as the level of income rose.

This paper proposes to adopt a novel econometric approach for estimating income and price elasticities for residential electricity demand, which allows to overcome the limitations of past studies in controlling for all possible outliers and structural breaks. The approach consists in specifying a general unrestricted error correction model for residential electricity demand, which we saturate with T Impulse and T Step Indicator dummies that control for all possible outliers and structural breaks that may have occurred over the period of observation. Estimation is made feasible by using the search algorithm Autometrics, which allows to conduct automatic model selection when there are more variables than observations, as is our case.

Table 1: Long-run and short-run elasticities in the literature on modelling residential electricity demand using aggregate data.

Study	Country & Time Period	Method	Explanatory Variables	Short-run income elasticity	Short-run price elasticity	Long-run income elasticity	Long-run price elasticity
Silk and Joutz (1997)	USA 1949-1993	Cointegration methods	income, electricity price, fuel oil price, HDD and CDD, interest rate.	0.39	-0.63	0.52	-0.48
Beenstock et al.(1999)	Israel 1973-1994	Cointegration methods	consumer spending, electricity price, HDD and CDD.			from 1.0 to 1.09	from -0.58 to -0.21
Filippini (1999)	Switzerland (40 cities) 1987-1990	Static Panel Data Methods	Local income tax revenue per household, electricity price, household size, number of households, HDD, dummy to control for different tariff.			0.33	-0.30
Fatai et al. (2003)	New Zealand 1960-1999	Cointegration methods	income, electricity price, price of substitute goods, temperature.	from 0.24 to 0.46	from -0.24 to -0.18	from 0.81 to 1.24	from -0.59 to -0.44
Holtedahl and Joutz (2004)	Taiwan 1955-1995	Cointegration methods	income, electricity price, oil price, urban population, CDD.	0.23	-0.15	1.57	-0.15
Hondroyiannis (2004)	Greece 1986-1999	Cointegration methods	income, electricity price, temperature.	0.2	statistically insignificant	1.56	-0.41
Narayan and Smyth (2005)	Australia 1969-2000	Cointegration methods	income, electricity price, natural gas price, temperature.	statistically insignificant	-0.26	0.32	-0.54
Halicioglu (2007)	Turkey 1968-2005	Cointegration methods	income, electricity price, urban population.	from 0.37 to 0.44	from -0.46 to -0.33	from 0.49 to 0.70	from -0.63 to -0.52
Narayan et al. (2007)	G7 countries 1978-2003	Cointegrated Panel Data Methods	income, electricity price, natural gas price.	statistically insignificant	-0.11	from 0.25 to 0.31	from -1.56 to -1.45
Amarawickrama and Hunt (2008)	Sri Lanka 1970-2003	Cointegration methods and STSM	income, electricity price.	from 1.82 to 1.96	statistically insignificant	from 0.99 to 1.96	from -0.06 to -0.02
Dergiades and Tsoulfidis (2008)	USA 1965-2006	Cointegration methods	income, electricity price, price of oil for heating purposes, HDD and CDD, occupied stock of housing.	0.1	-0.39	0.27	-1.07
Eskeland and Mideksa (2010)	31 European countries 1995-2005	Static Panel Data Methods	income, electricity price, HDD and CDD.			0.80	-0.20
Nakajima and Hamori (2010)	USA (48 states) 1993-2008	Cointegrated Panel Data Methods	income, electricity price, HDD and CDD.			from 0.33 to 1.00	from -0.34 to -0.12
Alberini and Filippini (2011)	USA (48 states) 1995-2007	Dynamic Panel Data Methods	income, electricity price, natural gas price, HDD and CDD.		from -0.15 to -0.08		from -0.73 to -0.44
Azevedo et al. (2011)	USA and EU 1990-2004	Static Panel Data Methods	consumer spending, electricity price, HDD.			statistically insignificant	from -0.25 to -0.21 (for USA) from -0.21 to -0.20 (for EU)
Filippini (2011)	Switzerland (22 cities) 2000-2006	Static and Dynamic Panel Data Methods	income, electricity price, household size, HDD and CDD.		from -0.835 to -0.652		from -2.266 to -1.273
Dilaver and Hunt (2011)	Turkey 1960-2008	STSM	income, electricity price.	0.38	-0.09	1.57	-0.38
Jamil and Ahmad (2011)	Pakistan 1961-2008	Cointegration methods	income, electricity price, diesel price, stock of capital, temperature.	statistically insignificant	statistically insignificant	1.97	-1.22
Blazquez et al. (2013)	Spain (47 provinces) 2000-2008	Dynamic Panel Data Methods	income, electricity price, household size, population, percentage of households with access to gas, HDD and CDD.	0.23	-0.07	0.61	-0.19
Atalla and Hunt (2016)	Gulf Cooperation Council Countries 1985-2012	STSM	income, electricity price, population, CDD and HDD.			from 0.43 to 0.71	from 0.16 to 0.00
Filippini et al. (2018)	USA (48 states) 1995-2011	Dynamic Panel Data Methods	income, electricity price, natural gas price, HDD and CDD, housing stock, dummy to control for electricity market liberalisation.		from -0.18 to -0.09		from -0.31 to -0.21
Cialani and Mortazavi (2018)	29 European countries 1995-2015	Dynamic Panel Data Methods	income, electricity price, population, CDD and HDD.	from 0.13 to 0.19	from -0.044 to -0.041	from 0.87 to 0.92	from -0.30 to -0.19
Csereklyei (2020)	European Union countries 1996-2016	Static and dynamic panel data methods	income, electricity price, population density, weather, ratio between environmental tax revenue and GDP	0.14	-0.08	0.61	from -0.56 to -0.55

3 Data and Econometric Methodology

3.1 Data Sources

The dataset used in this paper consists of annual time series collected for twelve major European countries: Austria, Belgium, Denmark, France, Germany, Ireland, Italy, Spain, Portugal, Sweden, the Netherlands and the UK for the period 1975-2018. The data are from the International Energy Agency (IEA, 2019) and the Eurostat (2020). The series are:

- Residential electricity consumption per capita in kWh (C_t): to construct these series the residential electricity consumption series from the IEA(2019) have been divided by the series of Population by the Eurostat (2020). The value of residential electricity consumption for 2018 is from the Eurostat (2020);

- Real gross domestic product per capita (2015 USD) (GDP_t): to construct these series the GDP series from the IEA(2019) have been divided by the series of Population by the Eurostat (2020);

- Real residential electricity price (2015 USD/kWh) (P_t): these are total prices from the IEA(2019);

- Heating Degree Days index (HDD_t) from the Eurostat (2020): the values are calculated as: if $T_i \leq 15°C$, then $HDD = \sum_i (18 - T_i)$ else $HDD = 0$, where T_i is the temperature in Celsius degrees,

- Cooling Degree Days index (CDD_t) from the Eurostat (2020): the values are calculated as: if $T_i \geq 24°C$, then $CDD = \sum_i (T_i - 21)$ else $CDD = 0$

3.2 Econometric Method

In this paper, we use automatic model selection, saturation methods and Autometrics to estimate the residential electricity demand for each of the twelve countries separately. Autometrics is a search algorithm implemented in the econometric software OxMetrics8 [1] that performs automatic model selection following the “Hendry” or “LSE” general-to-specific procedure (Doornik, 2009). This approach starts from the specification of a general unrestricted model (GUM) that incorporates everything that potentially matters in a relationship (i.e. variables, dynamic effects, breaks, outliers, nonlinearities, trends) and applies a sequence of reductions consisting in the elimination of variables that are statistically insignificant, so as to find a congruent and parsimonious model encompassing the GUM for representing the relationship under examination. When the GUM contains many variables, the reduction can be very time consuming to be undertaken manually, if not unfeasible in

[1] OxMetrics is a software for econometric analysis of time series, forecasting, financial econometric modelling, and statistical analysis of cross-section and panel data http://www.oxedit.com/products

the case when there are more variables than observations. Automatic selection algorithms are therefore necessary to perform this task. Doornik (2009) and Doornik and Hendry (2018) provide the details of Autometrics that this subsection briefly summarizes.

The Autometrics algorithm performs a tree search, where at the root of the tree there is the GUM while every branch of the tree represents a possible reduction path from the GUM. Thus, at every node and subnode of the tree there is a model containing fewer variables than the GUM. The search process starts from eliminating the most insignificant variable from the GUM and continues until the branch that started with the elimination of that variable has finished. When the reduction process is completed, the resulting model is called a terminal and Autometrics moves on to exploring another branch. The modeller chooses the so-called target size, which is the proportion of irrelevant variables that survive the reduction process. If a terminal does not pass the full battery of the diagnostic tests, then Autometrics backtracks until a valid model is found. The diagnostic tests are: the error autocorrelation test (Godfrey, 1978); the ARCH test (Engle, 1982); the Normality test (Doornik and Hansen, 1994); the heteroscedasticity test (White, 1980) and the RESET test (Ramsey, 1969).

Autometrics allows to add into automatic model selection impulse and/or step indicators for every data point in the sample so as to capture outliers and breaks. Impulse-Indicator Saturation (IIS) and Step-Indicator Saturation (SIS) are procedures to test for an unknown number of breaks, occurring at unknown times and are well documented in the literature by papers illustrating their theoretical properties and studies presenting interesting empirical applications (see inter alia Hendry, 1999; Santos et al., 2008; Johansen and Nielsen, 2009; Castle et al., 2011; Castle et al., 2012, Castle et al., 2015, Hendry and Doornik, 2014, Bergamelli and Urga, 2016 and Ericsson, 2017). IIS uses the zero–one impulse indicator dummies which are defined as $I_{i,t} = 1$ for $t = i$, zero otherwise to saturate a model. A model for a sample of T observations will include T of such dummies in its general unrestricted formulation. SIS uses one-off step dummies which are defined as $S_{i,t} = 1$ for $t \leq i$, zero otherwise. Step dummies are useful to capture permanent or long-lasting changes that are not otherwise incorporated into a specific empirical model.

The inclusion of T impulse and T step dummies for a sample of T observations generates by default a model with more variables than observations, making estimation unfeasible at first sight. However, estimation can be done since Autometrics creates blocks of dummies for subsets of observations, includes one block of dummies into the model, select those which are significant, repeats the process for another block of dummies, and finally re-estimates the model with the retained dummies from the different blocks and selects the statistically significant dummies from the combined set. Autometrics also offers as an option to set certain variables as "fixed", that is variables that are forced to be included in the final selected model and hence that cannot be deleted by the algorithm, even if they are not statistically significant.

For modelling residential electricity demand, we specify an unrestricted error correction model that contains both IIS and SIS. The general equation is:

$$\Delta lnC_t = \alpha_0 + \alpha_1 \Delta lnC_{t-1} + \alpha_2 \Delta lnGDP_t + \alpha_3 \Delta lnGDP_{t-1} + \alpha_4 \Delta lnP_t + \alpha_5 \Delta lnP_{t-1} + \alpha_6 \Delta lnHDD_t + \alpha_7 \Delta lnHDD_{t-1} + \alpha_8 \Delta lnCDD_t + \alpha_9 \Delta lnCDD_{t-1} + \beta_1 lnC_{t-1} + \beta_2 lnGDP_{t-1} + \beta_3 lnP_{t-1} + \beta_4 lnHDD_{t-1} + \beta_5 lnCDD_{t-1} + \sum_{i=1}^{T} \gamma_i I_{i,t} + \sum_{i=1}^{T} \delta_i S_{i,t} + \varepsilon_t \quad (1)$$

where ΔlnC_t is the annual rate of change of residential electricity consumption per capita, $\Delta lnGDP_t$ is the annual rate of change of GDP per capita, ΔlnP_t is the annual rate of change of residential electricity price, $\Delta lnHDD_t$ is the annual rate of change of HDD, $\Delta lnCDD_t$ is the annual rate of change of CDD, ΔlnC_{t-1}, $\Delta lnGDP_{t-1}$, ΔlnP_{t-1}, $\Delta lnHDD_{t-1}$ and $\Delta lnCDD_{t-1}$ are the one-year lagged rates of change of the relating variables, while lnC_{t-1}, $lnGDP_{t-1}$, lnP_{t-1}, $lnHDD_{t-1}$ and $lnCDD_{t-1}$ are the one-year lagged of the logs of residential electricity consumption per capita, GDP per capita, residential electricity price, HDD and CDD respectively. In running these regressions, we set the last four variables as "fixed".

The presence of a meaningful long-run relationship between the variables is checked by verifying that the coefficient associated with the lagged dependent variable in log-levels ($\hat{\beta}_1$) is statistically significant with negative sign (Dufour, 1997). The correct specification of the selected model is evaluated using the battery of diagnostic tests listed above. Finally, the long-run income and price elasticities are calculated.

4 Results and Discussion

Table 2 and Table 3 report the estimated models automatically selected by Autometrics for the twelve European countries. For each country considered, the final selected model is a congruent and parsimonious error correction model. The implementation of model saturation with IIS and SIS determines that the selected impulse and step indicator dummies capture anomalous events, i.e. outliers and breaks, that have featured the demand in a particular year.

In all models, the estimated coefficient of the error correction term $\hat{\beta}_1$ is statistically significant at the 1% significance level and negative, therefore indicating the presence of cointegration or long-run relationship between electricity consumption, income (as measured by GDP), price and the climate variables HDD and CDD. The estimated coefficients on income and price in log-levels, namely $\hat{\beta}_2$ and $\hat{\beta}_3$, are statistically significant for all countries at conventional significance levels, with exception of the estimated coefficient on the log-level of income for Germany. The coefficient on $lnHDD_{t-1}$, representing the impact of cold weather and hence the demand of electricity for heating purposes, is statistically significant for Germany, Denmark, France, Ireland, Italy, Spain and the UK, whereas the variable accounting for hot weather, namely $lnCDD_{t-1}$, is not statistically significant for most of the countries with the exception of Belgium, Germany and Spain, for which however the coefficients are quite small.

The short-run impact coefficients on income ($\hat{\alpha_2}$ and $\hat{\alpha_3}$) and price ($\hat{\alpha_4}$ and $\hat{\alpha_5}$) are statistically insignificant for most of the countries, since the variables in first difference are not retained in the final selected models. The coefficients associated to $\Delta lnHDD_t$, representing the estimated short-run impact of cold weather on electricity consumption are statistically significant for Austria, Belgium, Germany, Denmark, France, Ireland and the UK, whereas when we look at the short-rum impact of hot weather, namely the coefficients on $\Delta lnCDD_t$, for no country we a find a statistically significant coefficient. The finding that electricity demand is more sensitive to cold than to hot weather is in line with Cialani and Mortazavi (2018) who offer as an explanation the fact that in Europe periods of heating are generally longer than periods of when air conditioning is needed.

Table 4 reports the long-run income and price elasticities, calculated for each selected model by dividing the $\hat{\beta_2}$ (coefficient on GDP) and $\hat{\beta_3}$ (coefficient on price) by the relevant $\hat{\beta_1}$ (coefficient on electricity consumption at time t-1). We also report 95% confidence intervals to provide an indication of the uncertainty in estimates of the income and price elasticities. All the long-run income and price elasticities are statistically significant at the conventional 1% and 5% level, with the exception of income elasticity for Germany, which is not significant, and of income elasticity for Denmark, which is significant at the 10% level. In addition, all long-run elasticities have the expected sign, i.e. positive for income and negative for price. The width of the confidence interval reflects the different standard errors of the point estimates. The confidence interval of income elasticity of Austria is very large reflecting the relatively large standard error of the estimated coefficient on GDP, whereas the confidence interval of income elasticity of France is quite narrow because of the very small (relative to the coefficient size) standard errors of both the estimated coefficient on GDP and the estimated coefficient on electricity consumption. Long-run income elasticities are less than one for all countries, which suggests that electricity is a necessity good rather than a luxury good for European countries. The differences in income elasticities across countries can be explained by several idiosyncratic factors. A first factor is the different level of per-capita GDP of the countries. In particular, we observe that countries with a relatively lower per-capita GDP (in terms of average value over the years 1975-2018) feature a larger income elasticity than countries with a comparatively higher per-capita GDP. For example, Denmark has an average per-capita GDP (in 2015 US dollars) of $ 40,462 and a long-run income elasticity of 0.19, whereas Portugal has an average per-capita GDP (in 2015 US dollars) of $ 24,330 and a long-run income elasticity of 0.74. Figure 1 displays the relationship between long-run income elasticities and per-capita GDP from which it emerges a

Table 2: Estimation Results Austria, Belgium, Germany, Denmark, France, Ireland.

Austria		Belgium		Germany		Denmark		France		Ireland	
Variables	ΔlnC_at_t	Variables	ΔlnC_be_t	Variables	ΔlnC_de_t	Variables	ΔlnC_dk_t	Variables	ΔlnC_fr_t	Variables	ΔlnC_ie_t
I1981	-0.178***	S11984	-0.035***	S11990	0.155***	I1980	-0.058***	I1995	-0.048***	I1990	-0.069***
	(0.018)		(0.007)		(0.012)		(0.017)		(0.006)		(0.012)
I1987	0.236***	S11986	-0.016**	S11991	-0.135***	S11982	-0.081***	I2003	0.028***	I1999	0.048***
	(0.017)		(0.007)		(0.013)		(0.014)		(0.005)		(0.012)
S12002	0.031***	S12001	-0.044***			S12016	0.041***	I2005	-0.068***	I2009	-0.043***
	(0.009)		(0.008)				(0.012)		(0.005)		(0.012)
		S12002	0.065***					I2011	-0.025***	S11982	-0.039***
			(0.008)						(0.008)		(0.009)
		S12005	0.144***					I2014	-0.046***	S12001	0.045***
			(0.008)						(0.007)		(0.013)
		S12006	-0.060***					I2017	-0.022***	S12002	-0.078***
			(0.011)						(0.006)		(0.014)
		S12007	0.082***					S11981	-0.075***		
			(0.010)						(0.006)		
		S12008	-0.091***					S11989	-0.023***		
			(0.010)						(0.006)		
		S12009	0.049***					S11990	0.034***		
			(0.010)						(0.008)		
		S12010	-0.021**					S11991	-0.036***		
			(0.009)						(0.006)		
		S12014	0.029***					S12009	-0.041***		
			(0.006)						(0.004)		
		S12017	-0.044***								
			(0.009)								
								ΔlnC_fr_{t-1}	-0.430***		
									(0.034)		
								ΔlnP_fr_t	-0.387***	ΔlnP_ie_t	-0.294***
									(0.033)		(0.035)
ΔlnC_at_{t-1}	0.192***	$\Delta lnGDP\_be_{t-1}$	-0.301**					$\Delta lnHDD\_fr_t$	0.316***	ΔlnP_ie_{t-1}	0.154***
	(0.054)		(0.109)						(0.013)		(0.033)
$\Delta lnHDD\_at_t$	0.185***	$\Delta lnHDD\_be_t$	0.175***	$\Delta lnHDD\_de_t$	0.186***	$\Delta lnHDD\_dk_t$	0.167***	$\Delta lnHDD\_fr_{t-1}$	0.187***	$\Delta lnHDD\_ie_t$	0.211***
	(0.040)		(0.016)		(0.021)		(0.028)		(0.016)		(0.033)
lnC_at_{t-1}	-0.109***	lnC_be_{t-1}	-0.269***	lnC_de_{t-1}	-0.121***	lnC_dk_{t-1}	-0.255***	lnC_fr_{t-1}	-0.324***	lnC_at_{t-1}	-0.243***
	(0.036)		(0.030)		(0.031)		(0.046)		(0.016)		(0.041)
$lnGDP\_at_{t-1}$	0.101**	$lnGDP\_be_{t-1}$	0.159***	$lnGDP\_de_{t-1}$	0.020	$lnGDP\_dk_{t-1}$	0.049*	$lnGDP\_fr_{t-1}$	0.129***	$lnGDP\_ie_{t-1}$	0.059***
	(0.044)		(0.028)		(0.024)		(0.029)		(0.017)		(0.017)
lnP_at_{t-1}	-0.083**	lnP_be_{t-1}	-0.079***	lnP_de_{t-1}	-0.043***	lnP_dk_{t-1}	-0.089**	lnP_fr_{t-1}	-0.086***	lnP_ie_{t-1}	-0.195***
	(0.036)		(0.024)		(0.015)		(0.036)		(0.015)		(0.022)
$lnHDD\_at_{t-1}$	-0.048	$lnHDD\_be_{t-1}$	0.025	$lnHDD\_de_{t-1}$	0.076***	$lnHDD\_dk_{t-1}$	0.154***	$lnHDD\_fr_{t-1}$	0.132***	$lnHDD\_ie_{t-1}$	0.110***
	(0.032)		(0.017)		(0.020)		(0.025)		(0.017)		(0.018)
$lnCDD\_at_{t-1}$	0.001	$lnCDD\_be_{t-1}$	0.002***	$lnCDD\_de_{t-1}$	0.003*	$lnCDD\_dk_{t-1}$	-0.001	$lnCDD\_fr_{t-1}$	-0.002	$lnCDD\_ie_{t-1}$	-0.001
	(0.003)		(0.001)		(0.002)		(0.001)		(0.001)		(0.002)
Observations	42	Observations	42	Observations	42	Observations	42	Observations	42	Observations	41
R-squared	0.937	R-squared	0.989	R-squared	0.912	R-squared	0.811	R-squared	0.996	R-squared	0.944

Standard errors in parentheses
*** p0.01, ** p0.05, * p0.1

Table 3: Estimation Results Italy, Netherlands, Spain, Portugal, Sweden, UK.

Italy		Netherlands		Spain		Portugal		Sweden		UK	
Variables	ΔlnC_it_t	Variables	ΔlnC_nl_t	Variables	ΔlnC_es_t	Variables	$D\Delta lnC\_pt_t$	Variables	ΔlnC_sw_t	Variables	ΔlnC_uk_t
I1982	0.028***	I1977	-0.039***	I1977	-0.050***	I2016	0.068**	I1985	0.137***	S11998	0.047***
	(0.009)		(0.009)		(0.011)		(0.028)		(0.034)		(0.009)
I2011	0.036***	I1981	-0.027***	I1979	0.039***	S11983	-0.102***	I2010	0.129***	S12002	-0.032***
	(0.009)		(0.008)		(0.009)		(0.024)		(0.034)		(0.009)
I2013	-0.027***	I1982	-0.031***	I1982	-0.054***	S12010	0.052***			S12014	0.035***
	(0.009)		(0.008)		(0.008)		(0.015)				(0.011)
I2014	-0.052***	S11987	0.097***	I1984	0.052***	S12014	-0.060***				
	(0.009)		(0.008)		(0.008)		(0.020)				
S11978	-0.026***	S11988	-0.071***	I1985	-0.028***						
	(0.009)		(0.011)		(0.009)						
S11983	-0.064***	S11989	0.055***	I1988	-0.039***						
	(0.008)		(0.010)		(0.008)						
		S11990	-0.036***	I2000	-0.111***						
			(0.007)		(0.008)						
		S12013	0.031***	S11992	-0.039***						
			(0.004)		(0.006)						
				S12006	0.030***						
					(0.007)						
				S12008	-0.087***						
					(0.007)						
				S12012	0.078***						
					(0.006)						
				S12017	-0.085***						
					(0.009)						
				Constant	-0.702**						
					(0.326)						
				ΔlnC_es_{t-1}	-0.483***					ΔlnP_uk_t	-0.239***
					(0.042)						(0.050)
$\Delta lnGDP\_it_{t-1}$	-0.548***			$\Delta lnGDP\_es_t$	1.411***					$\Delta lnHDD\_uk_t$	0.263***
	(0.097)				(0.089)						(0.028)
lnC_it_{t-1}	-0.463***	lnC_nl_{t-1}	-0.341***	lnC_es_{t-1}	-0.169***	lnC_pt_{t-1}	-0.151***	lnC_sw_{t-1}	-0.167***	lnC_uk_{t-1}	-0.404***
	(0.054)		(0.071)		(0.023)		(0.031)		(0.040)		(0.070)
$lnGDP\_it_{t-1}$	0.354***	$lnGDP\_nl_{t-1}$	0.217***	$lnGDP\_es_{t-1}1$	0.120***	$lnGDP\_pt_{t-1}$	0.112***	$lnGDP\_sw_{t-1}$	0.135**	$lnGDP\_uk_{t-1}$	0.205***
	(0.045)		(0.043)		(0.039)		(0.039)		(0.053)		(0.036)
lnP_it_{t-1}	-0.072***	lnP_nl_{t-1}	-0.028**	lnP_es_{t-1}	-0.118***	lnP_pt_{t-1}	-0.114***	lnP_sw_{t-1}	-0.112***	lnP_uk_{t-1}	-0.246***
	(0.019)		(0.012)		(0.011)		(0.036)		(0.036)		(0.030)
$lnHDD\_it_{t-1}$	-0.077***	$lnHDD\_nl_{t-1}$	0.006	$lnHDD\_es_{t-1}$	0.063***	$lnHDD\_pt_{t-1}$	-0.046	$lnHDD\_sw_{t-1}$	-0.030	$lnHDD\_uk_{t-1}$	0.055**
	(0.017)		(0.015)		(0.020)		(0.032)		(0.051)		(0.024)
$lnCDD\_it_{t-1}$	-0.002	$lnCDD\_nl_{t-1}$	0.001	$lnCDD\_es_{t-1}$	0.019**	$lnCDD\_pt_{t-1}$	0.018	$lnCDD\_sw_{t-1}$	-0.001	$lnCDD\_uk_{t-1}$	-0.001
	(0.005)		(0.001)		(0.007)		(0.012)		(0.002)		(0.001)
Observations	42	Observations	42	Observations	42	Observations	42	Observations	42	Observations	42
R-squared	0.950	R-squared	0.921	R-squared	0.983	R-squared	0.862	R-squared	0.660	R-squared	0.873

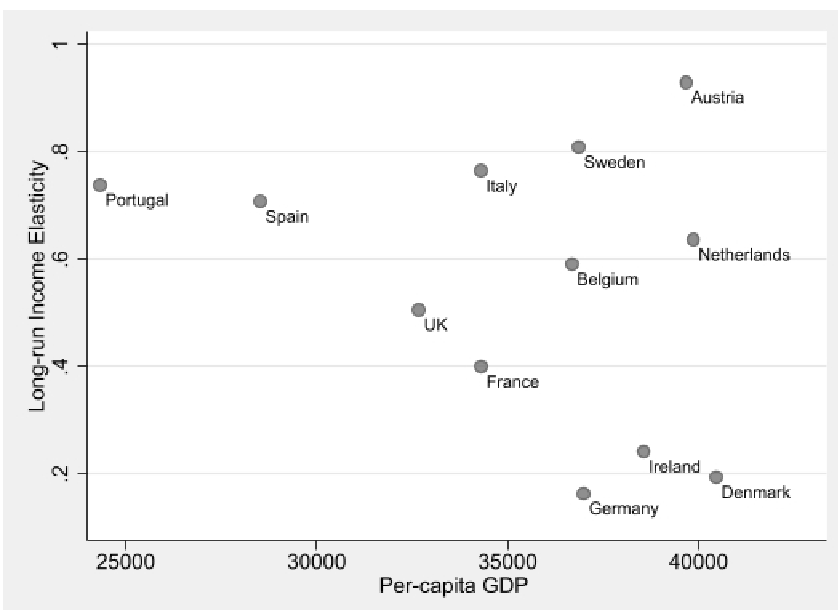
Standard errors in parentheses
*** p0.01, ** p0.05, * p0.1

Table 4: Estimated long-run income and price elasticities and related 95% confidence intervals.

	Long-run Income Elasticity	[95% Conf. Interval]	Long-run Price Elasticity	[95% Conf. Interval]
Austria	0.930	[0.064 5.375]	-0.760	[-0.858 -0.258]
Belgium	0.591	[0.305 1.051]	-0.295	[-0.389 -0.144]
Denmark	0.194	[-0.026 0.671]	-0.347	[-0.462 -0.097]
France	0.400	[0.265 0.565]	-0.266	[-0.326 -0.192]
Germany	0.164	[-0.161 1.219]	-0.354	[-0.391 -0.231]
Ireland	0.242	[0.074 0.586]	-0.803	[-0.937 -0.737]
Italy	0.765	[0.459 1.260]	-0.155	[-0.191 -0.095]
Netherlands	0.637	[0.266 1.559]	-0.081	[-0.108 -0.014]
Portugal	0.739	[0.152 2.178]	-0.755	[-0.874 -0.465]
Spain	0.708	[0.180 1.664]	-0.699	[-0.785 -0.651]
Sweden	0.809	[0.112 2.819]	-0.668	[-0.748 -0.439]
UK	0.506	[0.241 1.057]	-0.607	[-0.703 -0.562]

negative relationship between the two variables, the only exceptions being Austria and Sweden. This result is consistent with the finding of Fouquet (2014) that income elasticity declines as income increases due to saturation effect, namely with greater income, consumption of goods increases only moderately. A second factor relates

Figure 1: Relationship between long-run income elasticities and per-capita GDP (average value 1975-2018 in 2015 US $).



to the different energy efficiency scores achieved by countries. Figure 2 reports the overall energy efficiency scores for households calculated over the period 2000-2018 from the ODYSSEE-MURE Database[2]. The overall energy efficiency score gives a snapshot of the current energy efficiency level reached by a country. The scores are calculated on three energy efficiency criteria: the energy efficiency level, the energy efficiency progress and the energy efficiency policies. For each of the three criteria each country is scored between 0 and 1 on the basis of a variety of indicators (extracted from the ODYSSEE Database) and of energy policies (extracted from the MURE Database), the overall energy efficiency score is an average of the scores for each criteria. Figure 3 shows that countries that score the highest (i.e. Ireland, UK, France) feature a long-run income elasticity smaller than 0.5, whereas countries that score the lowest (i.e. Italy, Portugal, Austria, Sweden) display the largest long-run income elasticity. This could be interpreted as that for countries that have effectively implemented energy efficiency policies and have a newer stock of appliances as income rises, consumption of electricity will increase only moderately.

Residential electricity demand for all countries is price inelastic not only in the short-run but also in the long-run, as the calculated long-run price elasticities always have an absolute value of less than one. This is not a surprise given that electricity is an essential good which can be substituted by natural gas only for heating and cooking services. The differences in long-run price elasticities across countries are due to idiosyncratic factors, most importantly limited possibility to substitute electricity with other fuels for some services.

Overall, the differences in long-run income and price elasticities across countries highlight that despite the implementation of several reforms to achieve a common market and to improve energy efficiency standards at EU-level, idiosyncratic components still prevail, such as different per-capita income level and different energy efficiency levels attained.

We can compare the estimated elasticities in this study against those reported in the literature on European countries. The average of the estimated income elasticities in our study is 0.56, which is in line with the value of 0.61 reported in Csereklyei (2020), but smaller than the range of 0.87-0.92 reported in Cialani and Mortazavi (2018) and the 0.8 value found by Eskeland and Mideksa (2010). The estimated income elasticity in our study for Spain is slightly larger than that found by Blázquez et al. (2013), which is 0.61. The average price elasticity in this study is -0.48, which is slightly smaller than -0.53 in Csereklyei(2020) but larger than the findings in Cialani and Mortazavi (2018), where the value of long-run price elasticity ranges from -0.30 and -0.19. Our estimate of price elasticity is also larger than the -0.20 reported by Eskeland and Mideksa (2010). The estimated price elasticity

[2] The ODYSSEE-MURE database provides detailed energy consumption by end-use (heating, appliances, solar penetration, other thermal uses), energy efficiency and CO2 related indicators as well as energy efficiency policy measures by sector for EU countries, Norway, Serbia, Switzerland and the United Kingdom. The data are available from 2000 only. https://www.odyssee-mure.eu/

in this study for Spain is larger than that found by Blázquez et al. (2013), which is -0.19. As pointed out by meta-analyses research (see among others Espey and Espey, 2004 and Labandeira et al., 2017) differences in estimated elasticities may be due to several factors, including the specification of the demand model and the estimation method, the type of data (i.e. time series versus cross-section or panel data), the type of consumer, the country and the sample period and the type of outlet where the paper has been published.

As residential electricity demand is price inelastic for all twelve countries, any policy aimed at energy conservation using only price increases as an instrument would have a limited effect on reducing electricity consumption, while causing a heavy loss in consumer welfare. Hence, to meet the long-term goals of decarbonisation, the EU policy makers should continue on the pathway of increasing energy efficiency of appliances and buildings, and of improving consumers' awareness and education to environmentally friendly habits.

Figure 2: Overall energy efficient scores for households of 12 European countries (2000-2018). Source: Enerdata (2021). ODYSSEE-MURE Database.

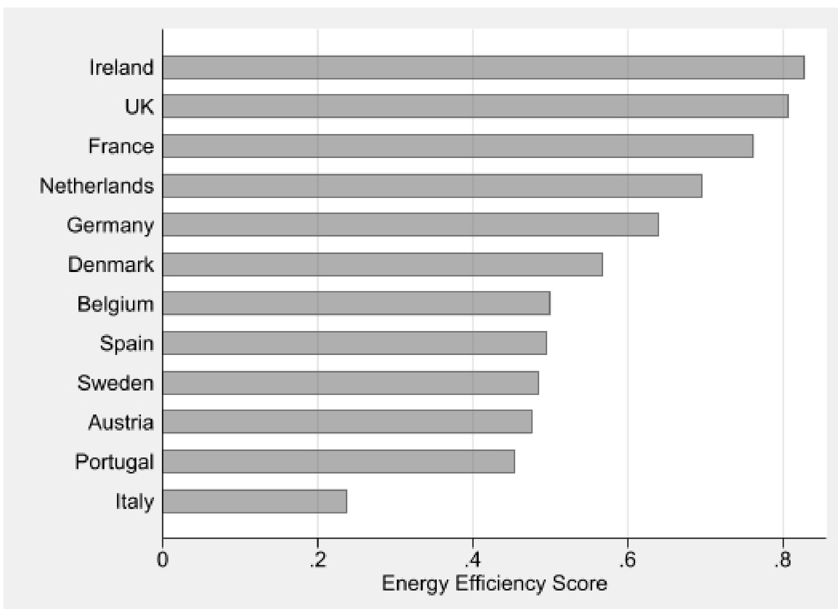
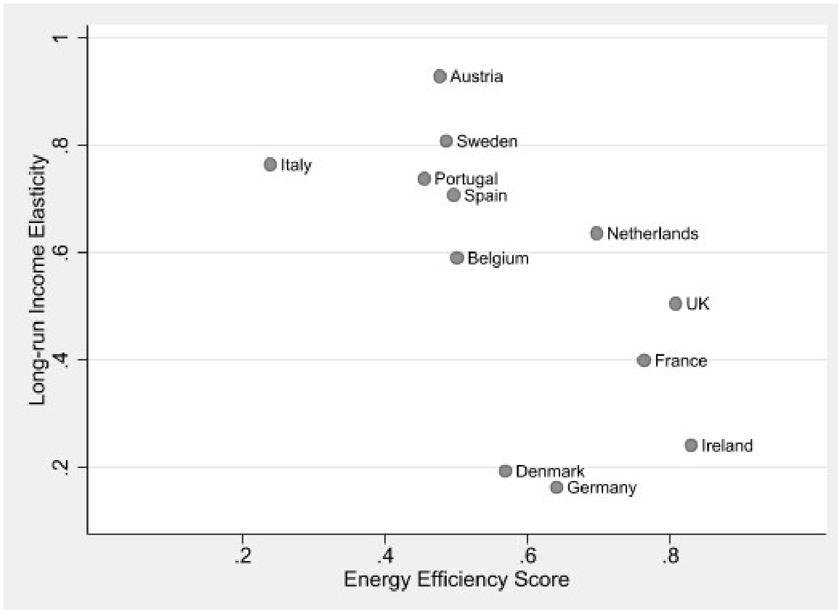


Figure 3: Relationship between long-run income elasticities and energy efficiency scores.



5 Conclusions

The aim of this paper was to contribute to the literature on estimating income and price elasticities for residential electricity demand by adopting a novel econometric approach that consists in using automatic model selection, saturation methods and Autometrics. This approach allowed to get consistent estimates of elasticities by automatically selecting all the relevant variables that affect electricity demand as well as outliers and breaks.

The residential electricity demand was estimated for Austria, Belgium, France, Germany, Denmark, Ireland, Italy, Spain, Portugal, the Netherlands, Sweden and the UK, using annual time series for 1975-2018. The final selected model for each country was a correctly specified error correction model, from which it emerged a cointegrating relationship between electricity consumption, income, electricity price and the climate variables HDD and CDD, once that impulse and step dummies were incorporated into the specification to capture outliers and breaks occurring at unknown times. The long-run income and price elasticities of residential demand unveiled similarities between major European countries, given that electricity was found to be a normal good (with estimated long-run income elasticity smaller than one) and price inelastic for all twelve countries. In particular, the estimated long-run income elasticities ranged between 0.93 (Austria) and zero (Germany), while long-run price elasticities were found to be between -0.80 (Ireland) and -0.08 (the

Netherlands). The results showed differences in the estimated elasticities across countries, which can be attributed to differences in per-capita GDP and in energy efficiency levels attained. Residential electricity demand being price inelastic bears important consequences on the choice of the most effective policy tool to promote energy conservation in Europe. Any policy based exclusively on price increases (e.g.energy taxes) could produce a heavy loss in consumers' welfare, discouraging consumption only marginally. EU decision makers should therefore continue to focus on promoting alternative energy efficiency policies to increase energy saving.

The main findings in this paper suggest interesting developments. First, the empirical analysis could be extended to all other countries in Europe to investigate further whether and to what extent commonalities in households' electricity consumption exist across the European area. In addition, this method could be applied to model the industrial electricity demand. Finally, the results of this study could be used to build a full cost-benefit analysis to evaluate alternative policy options to achieve the EU's long-term decarbonisation target. These developments are left to future work.

6 References

Alberini, A. and M. Filippini (2011). "Response of residential electricity demand to price: the effect of measurement error." Energy Economics 33, 889-895.

Alberini, A., Gans, W. and D. Velez-Lopez (2011). "Residential consumption of gas and electricity in the US: the role of prices and income." Energy Economics 33, 870-881.

Amarawickrama, H.A. and L.C. Hunt (2008). "Electricity demand for Sri Lanka: a time series analysis." Energy 33, 724-739.

Arora, S. and J.W. Taylor (2013). "Short-term forecasting of anomalous load using rule-based triple seasonal methods." IEEE Transactions on Power Systems 28, 3235-3242.

Atalla, T.N. and L.C.Hunt (2016). "Modelling residential electricity demand in the GCC countries." Energy Economics 59, 149-158.

Azevedo, I.M., Morgan, M.G. and L. Lave (2011). "Residential and regional electricity consumption in the U.S. and E.U.: how much will higher prices reduce CO2 emissions?" Electricity Journal 24, 21-29.

Beenstock, M., E. Goldin and D. Nabot (1999). "The demand for electricity in Israel." Energy Economics 21, 168-183.

Bergamelli, M. and G. Urga (2016). "Detecting multiple structural breaks: dummy saturation vs sequential bootstrapping." Centre for Econometric Analysis, Cass Business School, Working Paper.

Bernard, J.T., Bolduc, D. and N.D. Yameogo (2011). "A pseudo-panel data model of household electricity demand." Resource and Energy Economics 33, 315-325.

Blázquez, L., N. Boogen and M. Filippini (2013). "Residential electricity demand in Spain: new empirical evidence using aggregate data." Energy Economics 36, 648-657.

Castle, J.L., Doornik, J.A. and D.F. Hendry (2011). "Evaluating automatic model selection." Journal of Time Series Econometrics 3, 1-31.

Castle, J.L., J.A. Doornik and D.F. Hendry (2012). "Model selection when there are multiple breaks." Journal of Econometrics 169, 239-246.

Castle, J. L., Doornik, J. A., Hendry, D. F. and F. Pretis. (2015). "Detecting location shifts during model selection by step-indicator saturation." Econometrics 3, 240-264.

Cialani, C. and R. Mortazavi (2018). "Household and industrial electricity demand in Europe." Energy Policy 122, 592-600.

Csereklyei, Z. (2020). "Price and income elasticities of residential and industrial electricity demand in the European Union." Energy Policy 137, 111079.

Dergiades, T. and L. Tsoulfidis (2008). "Estimating residential demand for electricity in the United States, 1965–2006." Energy Economics 30, 2722-2730.

Dilaver, Z. and L.C. Hunt (2011a). "Industrial electricity demand for Turkey: A structural time series analysis." Energy Economics 33, 426-436.

Dilaver, Z. and L.C. Hunt (2011b). "Modelling and forecasting Turkish residential electricity demand." Energy Policy 39, 3117-3127.

Doornik, J.A. (2009). Autometrics. In: J.L. Castle and N. Shephard, (eds.), *The Methodology and Practice of Econometrics.* Oxford University Press, 88-121.

Doornik, J. A. and H. Hansen (1994). "A practical test for univariate and multivariate normality. " Discussion paper, Nuffield College.

Doornik J.A. and D.F. Hendry (2018). *Empirical Econometric Modelling Using PcGive: Volume I.* Timberlake Consultants Press, London.

Dufour, J.M. (1997). "Some impossibility theorems in econometrics, with applications to structural and dynamic models." Econometrica 65, 1365-1389.

Enerdata (2021). ODYSSEE-MURE Database. https://www.odyssee-mure.eu/

Engle, R.F. (1982). "Autoregressive conditional heteroscedasticity, with estimates of the variance of United Kingdom inflation." Econometrica 50, 987-1007.

Engle, R., and C. Granger (1987). "Co-integration and error correction: representation, estimation and testing." Econometrica 55, 251-276.

Ericsson, N.R. (2017). "How biased are U.S. government forecasts of the federal debt?" International Journal of Forecasting 33, 543-559.

Eskeland, G.S. and T.K. Mideksa (2010). "Electricity demand in a changing climate." Mitigation and Adaptation Strategies for Global Change 15, 877-897.

Espey, J.A. and M. Espey (2004). "Turning on the lights: a meta-analysis of residential electricity demand elasticities." Journal of Agricultural and Applied Economics 36, 65-81.

European Commission (EC, 2015). "A Framework Strategy for a Resilient Energy Union with a Forward-Looking Climate Change Policy" COM(2015)080.

Eurostat (2020). “Energy statistical database.” https://ec.europa.eu/eurostat/web/energy/data

Fatai, K., L. Oxley and F.G. Scrimgeour (2003). “Modeling and forecasting the demand for electricity in New Zealand: a comparison of alternative approaches.” The Energy Journal 24, 75-102.

Filippini, M. (1999). “Swiss residential demand for electricity.” Applied Economic Letters 6, 533-538.

Filippini, M. (2011). “Short- and long- run time-of-use price elasticities in Swiss residential electricity demand.” Energy Policy 39, 5811-5817.

Filippini, M. and S. Pachauri (2004). “Elasticities of electricity demand in urban Indian households.” Energy Policy 32, 429-436.

Filippini, M., Hirl, B. and G. Masiero (2018). “Habits and rational behaviour in residential electricity.” Resource and Energy Economics 52, 137-152.

Fouquet, R. (2014). “Long-run demand for energy services income and price elasticities over two hundred years.” Review of Environmental Economics and Policy 8, 186-207.

Godfrey, L. G. (1978). “Testing for higher order serial correlation in regression equations when the regressors include lagged dependent variables.” Econometrica 46, 1303-1313.

Halicioglu, F. (2007). “Residential electricity demand dynamics in Turkey.” Energy Economics 29, 199-210.

Harvey, A.C. (1989). *Forecasting, Structural Time Series Models and the Kalman Filter*. Cambridge University Press.

Hendry, D.F. (1999). “An Econometric Analysis of US Food Expenditure, 1931-1989.” In: J.R. Magnus and M.S. Morgan, (eds.), *Methodology and Tacit Knowledge: Two Experiments in Econometrics*. John Wiley and Sons, 341-361.

Hendry, D.F. and J.A. Doornik (2014). *Empirical Model Discovery and Theory Evaluation*. MIT Press.

Hendry, D. F., Johansen, S. and C. Santos (2008). “Automatic selection of indicators in a fully saturated regression.” Computational Statistics 23, 337-339.

Holtedahl, P. and F.L. Joutz (2004). “Residential electricity demand in Taiwan.” Energy Economics 26, 201-224.

Hondroyiannis, G. (2004). “Estimating residential demand for electricity in Greece.” Energy Economics 26, 319-334.

Hong, T. and S. Fan (2016). “Probabilistic electric load forecasting: A tutorial review. ” International Journal of Forecasting 32, 914-938.

Hong, T., Pinson, P., Wang, Y., Weron, R., Yang, D., and H. Zareipour (2020). “Energy Forecasting: A Review and Outlook. ” IEEE Open Access Journal of Power and Energy 7, 376-388.

International Energy Agency (2019). “World Energy Prices. “UK Data Service. https://doi.org/10.5257/iea/wep/2019-05

Jamil, F. and E. Ahmad (2011). “Income and price elasticities of electricity demand: aggregate and sector-wise analyses.” Energy Policy 39, 5519-5527.

Johansen, S. (1988). "Statistical analysis of cointegration vectors." Journal of Economic Dynamics and Control 12, 231-254.

Johansen, S. and B. Nielsen (2009). "An Analysis of the indicator saturation estimator as a robust regression estimator." In: J.L. Castle and N. Shephard, (eds.), *The Methodology and Practice of Econometrics.* Oxford University Press, 1-36.

Krishnamurthy, C.K.B. and B. Kriström (2015). "A cross-country analysis of residential electricity demand in 11 OECD-countries." Resource and Energy Economics 39, 68-88.

Labandeira, X., Labeaga, J.M. and X. López-Otero (2017). "A meta-analysis on the price elasticity of energy demand." Energy Policy 102, 549-568.

Miller, M. and A. Alberini (2016). "Sensitivity of price elasticity of demand to aggregation, unobserved heterogeneity, price trends, and price endogeneity: evidence from U.S. data. " Energy Policy 97, 235-249.

Nakajima, T. and S. Hamori (2010). "Change in consumer sensitivity to electricity prices in response to retail deregulation: A panel empirical analysis of the residential demand for electricity in the United States." Energy Policy 38, 2470-2476.

Narayan, P.K. and R. Smyth (2005). "The residential demand for electricity in Australia: an application of the bounds testing approach to cointegration." Energy Policy 33, 467-474.

Narayan, P.K., R. Smyth and A. Prasad (2007). "Electricity consumption in G7 countries: a panel cointegration analysis of residential demand elasticities." Energy Policy 35, 4485-4494.

Pesaran, M.H. and Y. Shin (1999). "An autoregressive distributed lag modelling approach to cointegration analysis." In: S. Strom, (ed.), *Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium.* Cambridge University Press.

Pesaran, M.H., Y. Shin and R.J. Smith (2001). "Bounds testing approaches to the analysis of level relationships." Journal Applied Econometrics 16, 289-326.

Ramsey, J.B. (1969). "Tests for specification errors in classical linear least squares regression analysis." Journal of the Royal Statistical Society B 31, 350-371.

Santos, C., D.F. Hendry and S. Johansen (2008). "Automatic selection of indicators in a fully saturated regression." Computational Statistics 23, 317-335.

Schulte, I. and P. Heindl (2017). "Price and income elasticities of residential energy demand in Germany." Energy Policy 102, 512-528.

Silk, J.I. and F.L. Joutz (1997). "Short and long-run elasticities in US residential electricity demand: a co-integration approach." Energy Economics 19, 493-513.

Taieb, S.B., Taylor, J.W. and R. J. Hyndman (2021). "Hierarchical probabilistic forecasting of electricity demand with smart meter data." Journal of the American Statistical Association 116, 27-43.

Weron, R. (2006). *Modeling and Forecasting Electricity Loads and Prices: A Statistical Approach.* Wiley.

White, H. (1980). "A heteroskedastic-consistent covariance matrix estimator and a direct test for heteroskedasticity." Econometrica 48, 817-838.