No. 3 DOI: 10.5277/ord160305 2016

Edyta ROPUSZYŃSKA-SURMA¹ Magdalena WĘGLARZ¹

RESIDENTIAL ELECTRICITY CONSUMPTION IN POLAND

Key factors influencing electricity consumption in the residential sector in Poland have been identified. A fixed-effects model was used, which includes time effects, and a set of covariates, based on the model developed by Houthakker et al. This model estimates electricity demand by using lagged values of the dependent variable along with current and lagged values of electricity prices, and other variables that affect electricity demand such as: population, economic growth, income per capita, price of related goods, etc. The model has been identified according to the research results of the authors and those obtained by Bentzen and Engsted. The set of covariates was extended to the lagged electricity price given by a tariff (taken from two years previous to the time of interest) and heating degree days index, a very important factor in European Union countries, where the climate is temperate. The authors propose four models of residential electricity demand, for which a confidence interval of 95% has been assumed. Estimation was based on Polish quarterly data for the years 2003–2013.

Keywords: forecasting, demand forecasting, econometric model, electricity consumption, HDD index

1. Introduction

There is a growing interest in reducing electricity consumption in every sector of the economy. The residential sector is a substantial consumer of electricity in every country, being largely an undefined electricity sink, due to following reasons: (i) the sector includes a wide variety of structure: household size, geometries and thermal insulation materials, (ii) the behavior of inhabitants varies widely and can impact energy consumption by as much as 100% for a given house, (iii) detailed sub-metering of households' end-uses has a prohibitive cost [11], (iv) in Poland, data collection is very

¹Faculty of Computer Science and Management, Wrocław University of Science and Technology, Wybrzeże Wyspiańskiego 27, 50-370 Wrocław, e-mail addresses: edyta.ropuszynska-surma@pwr.edu.pl, magdalena.weglarz@pwr.edu.pl

difficult due to the low level of electricity metering (and, in particular, modern smart meters). Electricity consumption for other major sectors such as commercial, industrial and transportation, are better understood than the residential sector. The residential sector consumes secondary energy. Residential energy consumption in Poland was about 19% of total energy consumption in 2013 and has been at the same level for the last three years [2]. All over the world, energy consumption by the residential sector accounts for 16–50% of that consumed by all the sectors in a country [9].

There are a lot of different modeling techniques that can be utilized to estimate the energy consumption of the residential sector. Swam [11] grouped techniques used to model residential energy consumption into two categories: "top-down" and "bottom-up". In this article, we apply top-down techniques, i.e. econometric models. Top-down models utilize an estimate of the total energy consumption of the residential sector and other pertinent variables to attribute this energy consumption to various categories of the entire housing sector. Such models include macroeconomic and socioeconomic effects that could influence residential electricity consumption by individual end-users. Top-down models determine the effect on total energy consumption of ongoing long-term changes or transitions within the residential sector, primarily for the purpose of determining supply requirements. We chose an econometric model to estimate residential electricity consumption, since our aim was to predict total demand, which is strongly associated with historical energy consumption, meaning that accurate estimation of total demand is realistic.

2. Model of residential energy consumption

As in the model developed by Houthakker et al. [8], we assume that the model includes the price of electricity itself, price of a substitute and consumers' income as the key variables in microeconomic decisions regarding demand. The model also takes into account population and weather, which also affect energy demand. In this analysis, we use a fixed-effects model, which includes time effects, and a set of covariates. We define the model using the following fixed-effect specification:

$$Q_t^D = Q_{t-1}^D \gamma + X_t \beta + X_{t-1} \alpha + Y_t \tag{1}$$

where Q_t^D is energy demand in the residential sector in year t, Q_{t-1}^D is the lagged value of energy demand, X_t is a set of observed variables (e.g., energy prices, prices of substitutes, population, income) affecting energy demand, and X_{t-1} is the lagged values of these variables, Y_t is a set of indicator variables that capture additional effects or differences.

2.1. Identification of demand factors

The identification of factors affecting energy demand is very important to any further analysis. Our analysis complies with studies conducted in other European Union countries [5, 6, 10, 12, 13]. We explored data from varioys sources, e.g. data taken from the Polish Central Statistical Office (CSO) [2–4], and a survey by a foundation for energy effective-ness [7]. This survey, conducted in Poland in 2009, indicated various non-price factors that affect energy demand in individual households. The survey concerned individual households in rural areas. So, these factors are typical of households but not for the whole residential sector. The identification of non-price factors that affect energy demand in the residential sector was made on the basis of this survey and our own analysis.

Demand is usually strongly dependent on price, so the price of goods or services is often the most important factor affecting demand. Other factors, called non-price determinants, cause a shift in the demand curve, resulting in a new one. Such changes in demand can be caused by, e.g. changing the price of other goods or factors not related to the current price of any goods or services, non-price determinants. We specified three different non-price determinants of demand: (i) the prices of related goods (gas, coal), (ii) consumer income, (iii) population size.

The price of electricity is the most important factor affecting demand in the residential sector. From a household's point of view, the electricity price is not the price from the energy market, but the price set by the utility company that supplies energy to a consumer. In Poland, there are a few tariffs proposed especially for households. The most popular one is G-11. The G tariff is characterized by 1-time zone (the price of consumption is independent of the time of use) and independent of the voltage level, as well as the allowed capacity. The legislation of energy tariffs was changed according to the Energy Law Act of April 10th, 1997 and other specific legislation. Generally, such tariffs relate to services offered by a monopoly (the transmission and distribution of energy) and they are calculated by energy companies and then controlled and approved by the Polish Energy Regulatory Office (ERO). For a long time, such tariffs were charged to all consumers who did not have right to third-party-access (TPA). However, since July 1st, 2007 everybody has had this right, yet most households have not used it. For this type of consumer, it is a uniform tariff, which includes a charge for the distribution service and one for the energy consumed.

In the case of electricity, the problem of related goods is very interesting. In many papers and analyses, the assumption was made that electricity has no close substitutes. In certain cases, this is true, but in some areas of electricity use, such as water or household heating, we could replace electricity with coal, gas, biomass or other sources of primary energy. If we look at electricity more widely, we will see that electricity supplied by utility companies could be substituted by electricity produced in the residential sector from renewable energy sources. In our analysis, we assume that the substitutes for electricity are coal and gas. More appropriately, taking into account Polish conditions, the main substitute seems to be coal. It is a very popular fuel for water and household heating. However, there is a very strong correlation between the coal price and electricity price (Fig. 1). The electricity price and gas price are less strongly correlated. These correlation coefficients are equal to 0.99 and 0.96, respectively.

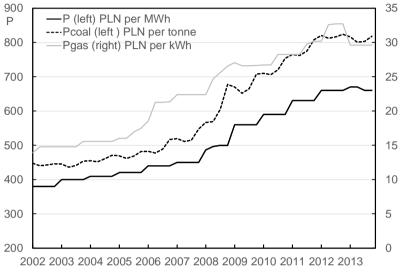


Fig. 1. Price of electricity and its substitutes in Poland (real data). Source: [3]

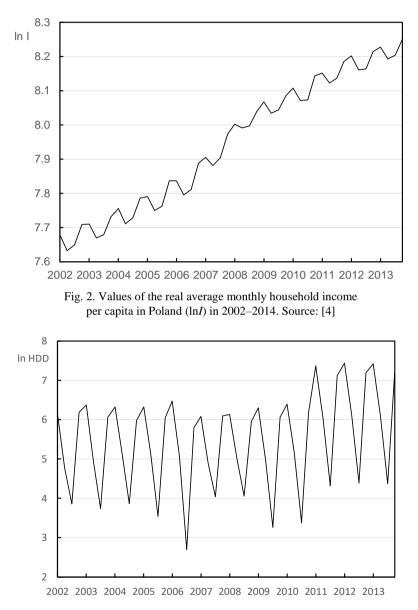
Generally, there is a positive correlation between energy consumption and all these variables: price of electricity, coal price and gas price. The results of the correlation study also reveal a strong correlation between income per capita and energy consumption (Table 1).

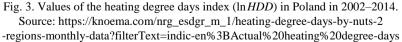
Table 1. Coefficient of linear correlation between energy consumption and other factors

Income	Price	Population	Gas price	Coal price	Heating degree days
0.90	0.87	0.57	0.90	0.86	0.33

Further analysis shows a very strong correlation between GDP and average monthly income per capita, as well as between GDP and usable floor area per capita. The first relationship must be strong, because of the definition of GDP and one of the methods for its measurement. GDP is the sum of all incomes in an economy, i.e. the income of all its citizens, enterprises and other institutions. When people are richer (have higher income), they buy more household goods (which need more energy, mainly electricity) and invest in residential estate. This process is consistent with Engel's law and

Törnquist's curve. Because of the strong correlations between GDP and income, as well as GDP and usable floor area per capita, we only take one of these variables – income per capita (Fig. 2) – as a factor determining energy demand.





Because these results are not satisfying, we modified the list of key factors that affect demand in the residential sector according to the results obtained by Bentzen and Engsted [1]. We included a fourth determinant, weather (which is obviously seasonal), that will be represented by the heating degree days (*HDD*) index. *HDD* is a quantitative factor determining the amount of energy which is consumed due to an increased need for household heating. *HDD* is measured relative to a baseline temperature, heating threshold – the outside temperature above which a building needs no heating. The most appropriate baseline temperature for any particular building depends on the temperature that the building is heated to, and the nature of the building (including the heat-generating occupants and equipment within it). *HDD* is calculated based on the daily average air temperature. The baseline temperature used in Poland is 18 °C and the observations of *HDD* over the period considered (using a logarithmic scale) are presented in Fig. 3.

In summary, the list of key factors that are included in the model is: the electricity price given by the G-11 tariff, price of gas given by the tariff for households, average monthly income per capita, population size, heating degree days index.

2.2. Proposed model

The model assumes that current demand partially adjusts to changes in the desired demand [8]. Energy demand does not fully adjust in the current period, because it is a stock-flow process. In this process, adjusting the stock usually takes more than one period but consumers can easily control the flow in the current period. Therefore, demand does not fully adjust to changes in desired demand within one period. Stock refers to the energy-consuming appliances that a consumer owns, such as a heater, stove, air conditioner. The flow indicates that the consumer uses these appliances. In this process, the consumer has immediate control over, e.g. where the thermostat is set, but this decision can only affect energy consumption to a limited degree. If the consumer expects larger changes in energy demand, he should replace a cheaper, inefficient heater with an expensive, efficient one, which typically cannot happen immediately.

The model we built is based on quarterly data, so time t-4 represents a lag of one year with respect to time t. We used logarithmic data. The first of the proposed models (called A) encompasses four exogenous variables:

$$Q_{t} = b + c_{1}Q_{t-4} + c_{2}I_{t-4} + c_{3}P_{t-4} + c_{4}Pop_{t-4} + c_{5}P_{t-4}^{s}$$
(2)

where Q_{t-4} is the lagged residential energy demand (from the previous year), I_{t-4} is the lagged average monthly income per capita, P_{t-4} is the lagged energy price given by the G-11 tariff, P_{t-4}^s is the lagged price of a related good (gas), Pop_{t-4} is the lagged population size.

In all cases, we adopted the method of elimination in our regression analysis. At each stage, we eliminated the variable which was least significant, always checking whether removing a variable does not excessively decrease the likelihood ratio for the new model. In first step, we removed the lagged value of the gas price and obtained Eq. (3). In the second step, the lagged value of income was insignificant, so the resulting model is given by Eq. (4) and is called model B. In the case of model A, we did not remove P_4 , because it leads to an excessive decrease in the likelihood ratio.

$$Q_{t} = b + c_{1}Q_{t-4} + c_{2}I_{t-4} + c_{3}P_{t-4} + c_{4}Pop_{t-4}$$
(3)

$$Q_{t} = b + c_{1}Q_{t-4} + c_{3}P_{t-4} + c_{4}Pop_{t-4}$$
(4)

During the elimination process, we obtained that the insignificant covariates were: gas price (substitute for electricity) and income. These results seem to be questionable. The results obtained in other countries [1, 5, 6, 10, 12, 13] indicated the strong dependence of residential energy consumption on gas price and income.

We assumed that households make their decisions rationally, so they can order the opportunities facing them from the most to the least preferred. Also, it is assumed that they can behave according these priorities in real life conditions. Households formulate their expectations about the future based on both past and current information, as well as information anticipated in the future. This assumption about rational expectations is the basis of many well-known economic theories such as rational expectation theory and cognitive adaptation theory. We assume that, when making decisions about electricity consumption, households rely on past information about the electricity price. In Poland, most households have not used the right to TPA and the electricity price is given by a tariff that is constant over a calendar year. We noticed that neither the price of electricity from a year ago nor from two years ago have an influence on household decisions. There is no association between current electricity price and electricity consumption.

We decided to assess the significance of exogenous variables including HDD (logarithmic values) and the lagged value of the electricity price – we considered the price from two years ago. The demand at time *t* is given by equation which defines model C:

$$Q_{t} = b + c_{1}Q_{t-4} + c_{2}I_{t-4} + c_{3}P_{t-4} + c_{4}Pop_{t-4} + c_{5}P_{t-4}^{s} + c_{6}HDD_{t} + c_{7}P_{t-8}$$
(5)

where HDD_t is the heating degree days index at time *t*, P_{t-8} is the electricity price at time *t*-8 (two years before).

As before, we removed insignificant variables step by step. The final model obtained (called D) is given below by the equation:

$$Q_{t} = b + c_{1}Q_{t-4} + c_{2}I_{t-4} + c_{3}P_{t-4} + c_{5}P_{t-4}^{s} + c_{7}P_{t-8}$$
(6)

This time, the elimination process indicated that the irrelevant covariates were the population size and heating degree days index.

3. Residential electricity consumption in Poland

In this section, we use the above approach to estimate residential electricity consumption in Poland. This estimation was based on quarterly data from 2003 to 2013. We estimated the coefficients for the four models presented above. In the first step, we estimated the coefficients for model A, and the results are presented in Table 2. The analysis was carried out using the Gretl program.

Variable	Coefficient	Standard error	T statistic	<i>p</i> -value
const	49.3032	17.1911	2.8679	0.00671
1_P_4	0.118853	0.069701	1.7052	0.09632
l_Pop_4	-2.50406	0.98427	-2.5441	0.01514
l_Income_4	0.0419332	0.0690782	0.6070	0.54743
1_Pgas_4	0.0297603	0.0360982	0.8244	0.41484
l_Demand_4	0.339321	0.0648786	5.2301	< 0.00001

Table 2. Results of estimation for model A

The coefficient of determination (R^2) for this model is 0.950528, and the adjusted R^2 is 0.944019. The *F* statistic with degrees of freedom vector (5, 38) is equal to 146.023 (with *p*-value <0.00001). It follows from these statistics that the model gives a very good fit to the data. The result of the Durbin–Watson test (DW(6, 44) = 0.576687) showed that there was positive first-order autocorrelation between the residuals. The elimination of the insignificant variables (gas price and income) led us to model B. The results are presented in Table 3.

Table 3. Estimation results for model B

Variable	Coefficient	Standard error	T statistic	<i>p</i> -value
const	61.2254	15.0156	4.0775	0.00021
1_P_4	0.203225	0.0349452	5.8155	< 0.00001
1_Pop_4	-3.20588	0.851065	-3.7669	0.00053
1_Demand_4	0.362222	0.062394	5.8054	< 0.00001

These results show that energy consumption is not affected by income or the price of the substitute (gas). In Poland, gas is mainly used for water heating, as well as household heating. We could presume that the income effect is overcome by the substitution effect, but the substitution effect was too small. So the results are questionable.

The coefficient of determination (R^2) for this model is 0.94786, the adjusted R^2 is 0.943949. The likelihood ratios for these two models are: 128.142 for model A and 126.986 for model B. The likelihood ratio statistic is given by $LR = 2 \times (128.142 - 126.986) = 2.31$ and this value is lower than the critical value for the chi-square(2) distribution at the 5% significance level (5.99). The result of the *LR* test gives us the information that the difference in estimation accuracy between these two models is not statistically significant. Hence, the more parsimonious model (B) fits the data as well as the more complex model (A), and hence should be preferred. The *F* statistic with degrees of freedom vector (3, 40) is equal to 242.387 (with *p*-value < 0.00001). It follows from these statistics that the model gives a very good fit to the data. The result of the Durbin–Watson test (*DW*(4, 44) = 0.682) shows that there is positive first-order autocorrelation between the residuals.

We verified the accuracy of this model using the RESET test. We tested the hypothesis that the specification of the model is good. For model B, we obtain the following realization of the *F* statistic: F = 1.336, which we compared with the critical value for the *F*(2, 38) distribution at a significance level of 5% (3.245). The empirical value of the *F* statistic is lower than the critical value, thus we accept the above hypothesis, that the accuracy of the model is good.

Evaluation of multicollinearity was carried out using the *VIF* (variance inflation factor) coefficient. In the case of model B, the multicollinearity coefficients for all the independent variables are rather low (below 10, Table 4).

Variable name	VIF
1_Pop_4	2.827
1_P_4	9.347
1_Demand_4	5.646

Table 4. VIF for the explanatory variables in model B

We assessed the assumption of homoscedasticity for this model (i.e. the variance of the residuals is independent of the value of the explanatory variables) using White's test. For model B, we obtain the following results for the 44 residuals: the appropriate R^2 statistic is equal to 0.55, so the realization of the statistic for White's test is equal to 24.258. Because the realization of the statistic for White's test is greater than the critical value for the chi-square(9) distribution at a significance level of 5% (16.92), then we reject the hypothesis about homoscedasticity and assumed that there is heteroscedasticity. As a result of the above analysis, we used White's estimator for model B, applying the generalized least squares method with heteroscedasticity consistent standard errors. The results of estimation for model B1 are presented in Table 5.

Variable	Coefficient	Standard error	T statistic	<i>p</i> -value
const	47.662	7.80716	6.1049	< 0.00001
1_P_4	0.125169	0.0252788	4.9515	0.00001
l_Pop_4	-2.51534	0.441682	-5.6949	< 0.00001
l_Demand_4	0.557777	0.0802485	6.9506	< 0.00001

Table 5. Results of estimation for model B1

The coefficient of determination (R^2) for this model is 0.953484, The adjusted R^2 is 0.949995. The *F* statistic with degrees of freedom vector (3, 40) is equal to 273.304 (with *p*-value <0.00001). It follows from these statistics that the model gives a very good fit to the data. The result of the Durbin–Watson test (DW(4, 44) = 0.505) showed that there is positive first-order autocorrelation between the residuals. The values of the standard errors of the parameter estimates are generally smaller and the values of the *t* statistics larger, which indicates that the adjustment for heteroscedasticity led to an improved model. The chi-square goodness-of-fit test indicates that the residuals fit a normal distribution (chi-square(2) statistic = 13.6939, with *p*-value equal to 0.00106269).

The results based on models for a wide range of European Union countries and USA show that energy consumption is strongly affected by income. This relation is not reflected in the residential data for Poland. The selection of the model presented in [1] was based on two factors: (1) including weather conditions in the set of explanatory variables, since they have a great influence on residential electricity consumption, (2) using Danish data to develop a model (due to its proximity to Poland). In the next step, we estimated the coefficients for model C, and the results are presented in Table 6.

Variable	Coefficient	Standard error	T statistic	<i>p</i> -value
Const	34.7739	13.8756	2.5061	0.01748
1_P_4	0.15834	0.061534	2.5732	0.01492
1_P_8	-0.0573029	0.0674985	-0.8490	0.40222
l_Pop_4	-1.56032	0.796744	-1.9584	0.05895
l_Pgas_4	0.0338483	0.0261271	1.2955	0.20441
1_HDD	-0.00177863	0.00152909	-1.1632	0.25335
l_Income_4	0.103858	0.0572731	1.8134	0.07916
l_Demand_4	0.110047	0.0787805	1.3969	0.17206

Table 6. Results of estimation for model C.

The coefficient of determination (R^2) for this model is 0.973294, and the adjusted R^2 is 0.967452. The log-likelihood ratio is equal to 138.639 and is greater than for model A. The *F* statistic with degrees of freedom vector (7, 32) is equal to 166.606 (with *p*-value <0.00001). It follows from these statistics that the model gives a very good fit to the data. The result of the Durbin–Watson test (DW(8, 44) = 0.5078) showed that there is positive first-order autocorrelation between the residuals. We then modified the model, eliminating the insignificant variables: population and the heating degree days index. The results of the asymptotic statistical tests resulting from the removal of 1_*HDD* and 1_*Pop*_4 are respectively: chi-square(2) statistic 4.97, with *p*-value equal to 0.0834 and *F* statistic: F(2, 32) = 2.48, with value p = 0.0993. The *p*-values are greater than 0.05, so these variables are insignificant and removing them does not significantly decrease the likelihood ratio for this model. The results of estimation for model D are presented in Table 7.

Variable	Coefficient	Standard error	T statistic	<i>p</i> -value
const	7.60939	0.670688	11.3457	< 0.00001
1_P_4	0.184073	0.0616747	2.9846	0.00523
1_P_8	-0.153999	0.0527598	-2.9189	0.00619
1_Income_4	0.0784901	0.0459669	1.7075	0.09684
1_Pgas_4	0.0622842	0.0225777	2.7587	0.00928
1 Demand 4	0.155241	0.0779843	1.9907	0.05460

Table 7. Results of estimation for model D

The coefficient of determination for this model is 0.969149, the adjusted R^2 is 0.964612, and the likelihood ratio is equal to 135.753. The *F* statistic with degrees of freedom vector (5, 34) is equal to 213.614 (with *p*-value <0.00001). It follows from these statistics that the model gives a very good fit to the data. The result of the Durbin–Watson test (*DW*(6, 44) = 0.436) showed that there is positive first-order autocorrelation between the residuals. All variables are significant at the 10% level and only lagged income and lagged demand are not significant at the 5% level (see Table 7). The log-likelihood ratio for model C is equal to 138.639, and for model D is equal to 135.753. The likelihood ratio statistic for comparing these two models is LR = 2(138.639 - 135.753) = 5.77 and this value is less than the critical value for the chi-square(2) distribution at a significance level of 5% (5.99). So we may accept the removal of the two variables. The result of this *LR* test indicates that removing these two variables: population and the heating degree days index, does not have a statistically significant effect on the accuracy of estimation. Hence, model D fits the data as well as model C and is more parsimonious.

In the case of model D, the multicollinearity coefficients for all the independent variables are very high (above 10), cf. Table 8.

Variable	VIF
1_P_4	62.233
1_P_8	40.129
l_Income_4	31.305
1_Pgas_4	17.899
1_Demand_4	10.665

Table 8. VIF for the explanatory variables in model D

We verified the accuracy of the model using the RESET test. We tested the hypothesis that the specification of the model is good. For model B, we obtain the following results: F = 14.388, which we compare with the critical value of the F(2, 32) statistic at a significance level of 5% (3.295). The empirical value of the F statistic is greater than the critical value, thus we reject the above hypothesis, i.e., the accuracy of this model is not good.

We verified the homoscedasticity of the residuals using White's test. For model B, we obtain the following results for 40 observations: the appropriate R^2 statistic is equal to 0.32, so the statistic for White's test is equal to 12.79. Because the realization of the statistic for White's test is lower than the critical value for the chi-square(20) distribution at a significance level of 5% (31.41), then we can accept the hypothesis about the homoscedasticity of the residuals.

Finally, in order to estimate the parameters in model D, we used White's estimator, applying the generalized least squares method with heteroscedasticity consistent standard errors. The results of estimation for model D1 are presented in Table 9.

Variable	Coefficient	Standard error	T statistic	<i>p</i> -value
const	8.03563	0.382093	21.0306	< 0.00001
1_P_4	0.187807	0.0674992	2.7824	0.00874
1_P_8	-0.130281	0.0647327	-2.0126	0.05213
l_Income_4	0.0580993	0.0360261	1.6127	0.11606
l_Pgas_4	0.0695756	0.017475	3.9814	0.00034
l_Demand_4	0.11044	0.0430453	2.5657	0.01488

Table 9. Results of estimation for model D1

The coefficient of determination for this model is 0.984187, The adjusted coefficient of determination is 0.981862. The *F* statistic with degrees of freedom vector (5, 34) is equal to 423.234 (with *p*-value <0.00001). It follows from these statistics that the model gives a very good fit to the data. The result of the Durbin–Watson test (DW(6, 40) = 0.389) showed that there is positive first-order autocorrelation between the residuals. In this case, the values of the standard errors and of the *t* statistics decreased for all the variables, so heteroscedasticity was not negligible. The distribution of the residuals is similar to the normal distribution. The chi-square goodness-of-fit test

rejects the hypothesis of normality at the 5% level, but not at the 1% level (chi-square(2) = 6.369 with *p*-value = 0.04140).

Regarding the significance of the variable Income_4 (lagged income), we obtained a *p*-value bigger than 0.05, so we initially removed this variable from the model. However, further analysis based on the likelihood ratio test indicated that removing this variable leads to a statistically significant decrease in the accuracy of the estimates from the model. Hence, the final model selected included the lagged income.

4. Conclusions

The paper presents the first step of the research project *Modelling prosumers be*havior on the energy market, which was to carry out task No. 1: Initial analysis of the factors that characterize willingness to become a prosumer and influence the demand curve. We chose an econometric model to estimate residential electricity consumption, because we needed a method that would give a very accurate estimate the required supply. Demand is very strongly associated with historical energy consumption, which enables accurate prediction of demand.

The results obtained are in contrast with results obtained in other EU countries [5, 6, 10, 12, 13]. Direct use of models widely presented in the literature was not possible for our data for Poland, since demand for electricity is only partially adjusted in the current period. Full adjustment of the demand for electricity requires one or two periods, which was clearly visible in the case of electricity price.

The results obtained made us reassess our assumptions about residential electricity consumption in Poland. First of all, it is not affected by weather or population size. The result regarding population size is unsurprising, since the Polish population did not change much over the period of study. The result regarding the independence of demand with regard to the weather is unusual, especially in our climatic conditions, where we have four seasons and quite cold winters. The weather changes from year to year, one winter might be severe, but another mild. In neighboring countries, weather has a very strong influence on electricity consumption.

Secondly, residential electricity consumption is strongly affected by the lagged electricity price and lagged gas price. The results show that lagged prices are more important factors than income. This result was also unexpected.

Thirdly, residential electricity consumption is weakly affected by lagged income. This result is not consistent with the results obtained in other countries, where there is a very strong relation between income and energy consumption. This result might be connected with the low level of income in the Polish economy in comparison with other European Union countries. Our results regarding income elasticities are in contrast with those presented in [1], which finds that residential electricity consumption is strongly affected by income. Short-run income elasticity was estimated to lie in the interval from 0.444 to 0.642, in contrast to our results, where short-run income elasticity was estimated to lie in the interval from 0.058 to 0.103.

Acknowledgements

This work was supported by funds from the National Science Centre (NCN, Poland) through grant No. 2013/11/B/HS4/01070.

References

- [1] BENTZEN J., ENGSTED T., A revival of the autoregressive distributed lag model in estimating energy demand relationships, Energy, 2001, 26 (1), 45.
- [2] Central Statistical Office, *Energy consumption in households in 2012*, Warsaw 2014, available on: www.stat.gov.pl
- [3] Central Statistical Office, *Prices in the national economy 2014*, Warsaw 2015, available on: www.stat.gov.pl
- [4] Central Statistical Office, *Quarterly macroeconomic indicators*, available on: http://stat.gov.pl/en /poland-macroeconomic-indicators
- [5] DA SILVA P.G., KARNOUSKOS S., ILIC D., A survey towards understanding residential prosumers in smart grid neighborhoods, The third IEEE PES Innovative Smart Grid Technologies (ISGT) Europe, Berlin, Germany, 14–17 Oct. 2012, 1–8.
- [6] FARHAR B.C., Willingness to Pay for Electricity from Renewable Resources. A review of Utility Market Research, National Renewable Energy Laboratory NREL/TP.550.26148, July 1999.
- [7] Forum Future of Rural Energy in Europe, *The energy needs and deficiencies of rural and suburban communities in Poland*), Warsaw 2010, available on: http://www.slideshare.net/forumfreePL /potrzeby-i-braki-energetyczne-spoecznoci-wiejskich-i-podmiejskich-w-polsce
- [8] HOUTHAKKER H., VERLEGER P., SHEEHAN D., Dynamic demand analyses for gasoline and residential electricity, Am. J. Agr. Econ., 1974, 56 (2), 412.
- [9] SAIDUR R., MASJUKI H.H., JAMALUDDIN M.Y., An application of energy and exergy analysis in residential sector of Malaysia, Energ. Policy, 2007, 35 (2), 1050.
- [10] SCARPA R., WILLIS K., Willingness-to-pay for renewable energy. Primary and discretionary choice of British households' for micro-generation technologies, Energ. Econ., 2010, 32, 129.
- [11] SWAN L.G., UGURSAL V.I., Modeling of end-use energy consumption in the residential sector. A review of modeling techniques, Renew. Sust. Energ. Rev., 2009, 13, 1819.
- [12] TAYLOR L.D., The demand for electricity. A survey, Bell J. Econ., 1975, 6 (1), 74.
- [13] WOOD G., NEWBOROUGH M., Dynamic energy-consumption indicators for domestic appliances. Environment, behavior and design, Energ. Buildings, 2003, 821.

Received 31 December 2015 Accepted 15 September 2016