energies

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Forecasting Household Energy Consumption in European Union Countries: An Econometric Modelling Approach

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Abstract: The article raises issues regarding the consumption of energy from both fossil and renewable sources in households. The research was carried out on the basis of data obtained from the Eurostat database, which covered the period from 1995 to 2021 and concerned the European Union countries. Increasing energy consumption and, thus, increasing household expenses affect their standard of living. The purpose of the analysis was to construct two econometric models for electricity consumption. The first model referred to the consumption of energy from fossil sources and the second from renewable sources. A forecast of energy consumption in households was also constructed on the basis of estimated models. Econometric modelling methods (multiple regression) and time-series forecasting methods (linear regression method, exponential smoothing models) were applied for the study. Research shows that the main factor that models energy consumption in households, both from fossil and renewable sources, is the final consumption expenditure of households (Euro per capita). The set of indicators for the models varies depending on the type of energy source. The forecast shows that the share of energy consumption obtained from fossil sources will decrease systematically, while the share of energy consumption from renewable sources will continue to increase systematically.

Keywords: fossil fuels; renewable energy; econometric modelling; forecasting; exponential smoothing

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Citation: Chudy-Laskowska, K.; Pisula, T. Forecasting Household Energy Consumption in European Union Countries: An Econometric Modelling Approach. *Energies* **2023**, *16*, 5561. https://doi.org/10.3390/en16145561

Academic Editor: Seung-Hoon Yoo

Received: 10 July 2023
Revised: 17 July 2023
Accepted: 20 July 2023
Published: 23 July 2023

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1. Introduction

Nowadays, it is unimaginable to exist without the use of energy. More and more appliances are used in households that use energy. A few years ago, installing air conditioning at home was rare, and now it is common. More and more devices that were previously powered by manual power are now electrified, for instance, meat grinders, toothbrushes, or razors that are powered by electricity from the socket. Every person uses a refrigerator, a washing machine, or charges mobile phones almost every day. Therefore, energy consumption in households is constantly increasing. For this reason, energy saving and renewable energy consumption are major concerns for both developed and developing countries [1].

In 2020, energy expenditures in households in the European Union countries ranged from 2.3% in Luxembourg to 8.8% in Slovakia, while the EU average was 4.5% of all total expenditure (Table 1).

In addition to food, the cost of energy use is one of the biggest burdens on a household budget. Household members spend most of it on heating—about 64%, and a large part is spent on water heating and lighting—about 14% each. Meal preparation accounts for more than 6% of energy expenditure (Table 2).

Table 1. Expenditures on electricity, gas, and other fuels as a percentage of total household expenditures (2021) [2].

Country	(%)	Country	(%)	Country	(%)
Slovakia	8.8	Latvia	5.0	Italy	3.8
Poland	7.4	Croatia	4.9	Lithuania	3.8
Czechia	6.1	Greece	4.7	Spain	3.6
Sweden	5.7	France	4.7	Netherlands	3.3
Slovenia	5.4	Finland	4.7	Portugal	3.3
Belgium	5.3	Germany	4.3	Cyprus	3.2
Bulgaria	5.2	Austria	4.2	Ireland	3.1
Estonia	5.2	Hungary	4.0	Malta	2.4
Denmark	5.0	Romania	3.9	Luxembourg	2.3

Table 2. Structure of energy consumption in households in EU countries (2018) [3].

Structure of Energy Consumption	(%)
Space heating	63.6%
Water heating	14.1%
Lighting and appliances	14.8%
Cooking	6.1%
Space cooling	0.4%
Other	1%

Research shows that most households live in obsolete buildings [4]; therefore, energy awareness issues seem to be important. Many households strive to reduce the costs associated with energy consumption by using energy-saving equipment.

It is worth mentioning that the highest costs in the household budget are due to the use of a fridge-freezer (about 28%), slightly less residents spend on lighting and the use of small household appliances (about 20%), and about 19% is consumed by an electric cooker. The washing machine generates about 10% of the costs and the TV 6%. The least one has to pay for using a dishwasher is about 0.5% of the household budget.

In the structure of energy consumption in households (Figure 1), natural gas, renewables, and biofuels have the greatest importance in most EU countries. The exception is Poland, where this function is taken over by solid fuels, mainly hard coal and firewood. They were used most often for space heating (by 32.8% of households). These fuels are also used to heat water (22.5% of households) and much less often to cook meals (1.7%).

The most common use of gas for space heating is in Hungary (84.2%), the Netherlands (83.9%), Italy (59.9%), and Luxembourg (56.8%).

Households located in Portugal (86.8%), Croatia (63.4%), and Bulgaria (61.9%) use renewable energy sources to heat their rooms (Figure 1).

Over the course of several years, there has been a clear trend toward an increase in the share of electricity used from renewable sources and a visible decrease in the share of electricity consumption from traditional sources based on fossil fuels and from nuclear power plants.

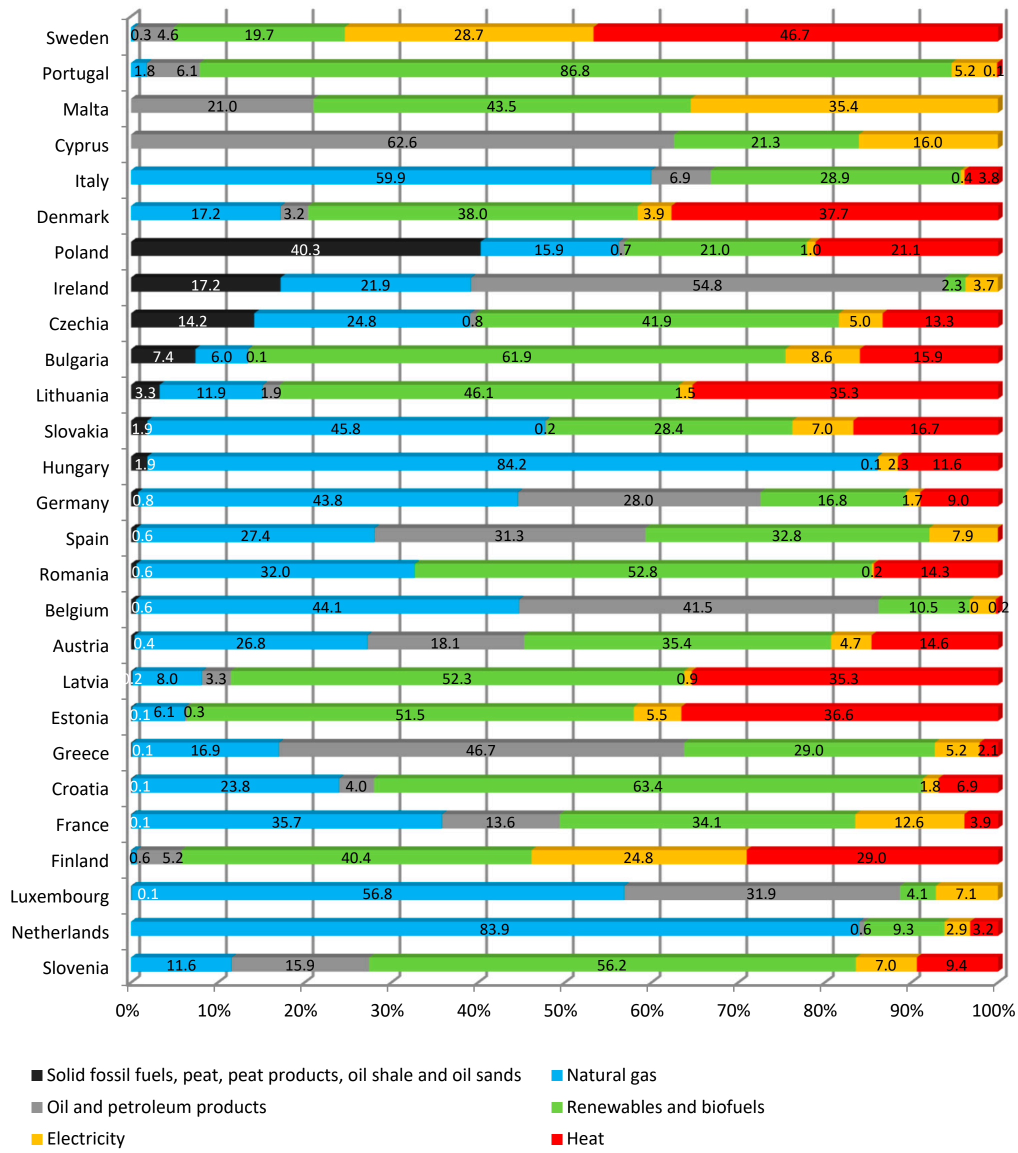

Figure 1. Share of fuels in the final consumption of the residential sector for space heating (2022) [5].

The strategy of gradually departing from obtaining energy from traditional fossil sources and nuclear sources has been implemented in EU countries over several years, and its effect is a gradual increase in the share of renewable energy in the structure of obtaining electricity from its various sources. The states united in the EU are obliged to do so on the basis of acts and agreements issued by the EU ("Clean Energy for All Europeans", "European Green Deal", and "Fit for 55") [6–12].

The purpose of the paper was to forecast changes in household energy consumption over time, both from fossil and renewable sources, obtained on the basis of two estimated econometric models. The first of the models describes what affects the consumption of energy from fossil sources in households and the second model the consumption of energy from renewable sources in households. The statistical data for the variables used in the models was obtained from the Eurostat database and covered the years from 1995 to 2021 (2021 was used to check the forecast accuracy of the regression models used), and these were the latest data that could be obtained during the analyses carried out.

In the research, two key research hypotheses were presented. The first hypothesis assumes that household consumption expenditure largely models final energy consumption for energy purposes (both from fossil and renewable sources). The second hypothesis, on the other hand, states that the sets of diagnostic variables modelling energy consumption for energy purposes in households differ depending on the sources from which this energy is obtained and that the share of energy consumption from renewable sources in the structure of energy consumption will systematically increase in the coming years in EU countries. The results of econometric analyses obtained for both considered models show that the following have a significant impact on the consumption of energy from traditional fossil sources: final consumption expenditure in households, average full-time adjusted salary per employee, and imported energy—lignite. On the other hand, the consumption of energy from renewable sources is also influenced by household expenses and also by completely different factors (specific only for renewable sources), such as primary energy production from wind and primary energy production from nuclear heat.

When analysing the literature on similar issues of forecasting energy consumption in households (which was analysed in detail in the next Section 2 of the paper), it can be noticed that there are no publications that would approach this issue in a similar way, i.e., describe and forecast the consumption of energy obtained from traditional fossil and ecological renewable sources in households in EU countries. This article attempts to fill this gap.

2. Literature Review

Many authors in their research undertake activities aimed at analysing the dependence of production, manufacturing, and consumption of energy obtained both from traditional sources of fossil fuels and renewables on many factors influencing it. The interdependence of energy production and consumption on economic development is mainly examined, taking into account many other additional factors, such as price, pandemic, sociological factors, etc. The impact of economic development on stimulating energy consumption in countries' economies is analysed, and the other way round, whether energy use affects in a beneficial way the economic development of countries. There are many publications that deal with such issues. Various types of econometric models of mutual influence are constructed, and on their basis, analyses of mutual interdependence are carried out using various analytical and research techniques.

These issues are addressed in [13–24]. Publication [13] examined the interdependence of economic development and energy consumption in the V4 countries using the autoregressive model VECM and the Granger causality test. Research shows that energy consumption contributes to the growth of GDP in the long term in countries such as Slovakia, Hungary, and the Czech Republic, whereas the research does not confirm such causality in Poland. In the work [14], an econometric model was described, which described the dependence of national income on the consumption of energy from various types of sources: fossil, renewable, and nuclear in 11 countries of Central and Eastern Europe. In the study, the technique of designing experiments using the Response Surface Method (RSM) and panel data regression was applied. 'A very strong relationship was confirmed between energy use and economic growth expressed as GDP.' In the publication [15], a similar study of the interdependence of economic development (GDP) and energy consumption in terms of electricity in households and industries in Romania was carried out in the situation of the COVID-19 pandemic. It was found that energy consumption in industry caused a strong increase in national income and stimulated the development of the country. The paper [16] analyses the mutual impact and interdependence of economic development (GDP) on energy consumption in 34 European countries (including EU 27) using the dynamic panel regression model (DPR). It was found that increasing production, both in the short and long term (increase in GDP), significantly increased electricity consumption. On the other hand, the relationship was not significant. Paper [17] analyses the relationship between energy consumption for electricity and economic development characterised by GVA (Gross Value Added) in the agricultural sector using the non-linear autoregressive distributed lag (NARDL) model in Baltic countries (Lithuania, Latvia, and Estonia). The study shows that energy consumption stabilises as the GVA increases. However, there is no indication that energy consumption will decrease after some time, 'thus the hypothesis for the inverse

U-shaped Energy Environmental Kuznets Curve (EEKC) is rejected'. In publication [18], using the Vector Autoregression model (VAR), the relationship between CO_2 greenhouse gas emissions, energy consumption from renewable and non-renewable sources, and nuclear energy was analysed along with GDP of three European countries (France, Spain, and Sweden). The interdependencies of these variables with GDP were examined in two phases that characterise the diffusion of renewable energy in the economies of countries (formative and expansion phase) using the Granger causality test. In the work [19,20], research was carried out on the relationship between the growth of national income (GDP growth) and five factors that characterise labour productivity, innovation in enterprises, and consumption of renewable energy in EU countries. The following hypothesis was proven: 'Renewable energy use at the EU level has a significant and strong impact on economic growth'. The interdependence of the national income on the consumption of renewable energy such as water, wind, solar, geothermal, and bioenergy was also examined using the ARDL autoregressive model. 'Renewable energy sources RES Energy: wind, solar, biomass, geothermal, and hydropower were shown to have a positive influence on economic growth at the EU level (biomass has the highest impact on economic growth)'. In [21], an analysis of the interdependence between energy consumption and factors characterising the level of urbanisation and economic growth (GDP) in China was carried out. The Granger causality test shows that there is a reciprocal two-way causal effect between energy consumption and economic growth, and that urbanisation causes an increase in energy consumption, and economic development contributes to more urbanisation. Many articles address the issue of the impact of the increasing share of renewable energy from various sources in the economy of the studied countries and their impact on their sustainable development [22–24]. Publication [22] examined the interdependence of national income per capita in EU countries (as a proxy for sustainable economic growth) based on the production of renewable energy from various sources using the Panel Vector Error Correction model (PVECM). 'It was shown that increasing the production of energy from renewable sources had a significant positive impact on the sustainable development of the country'. Similarly, works [23,24] examined the interdependence of the use and consumption of energy from renewable sources and the economic growth expressed by GDP in the OECD countries. The work [23] showed, among others, that the increase in national income per capita of countries had a positive effect on the increase in the use of renewable energy sources. On the other hand, in work [24], it was based on the study of the interdependence of energy consumption from renewable sources depending on national income (GDP) and the prices of coal and gas. Coal and gas prices have been observed to increase renewable energy consumption in the short term. There is a short-term causality from the price of coal and the price of natural gas to renewable energy consumption. There are many more publications on the interdependence between energy consumption and economic growth. A very comprehensive analysis of the literature in this field is presented in the paper [25].

From the point of view of practical applications, it is very important to study the dependence of energy consumption for various purposes on many factors that influence it. Several papers [26–29] deal with this type of issue. In [26], a logarithmic linear multiple regression model for the residential heating consumption econometric model was estimated in the UK and Germany. Similarly, in the next two studies, the dependence of electricity demand in households in Spain was examined using the partial adjustment model [27] and the log-linear regression model [28] in the years immediately after the global economic crisis. The publication [29] analyses the dependence of electricity consumption in Portugal on municipalities and households depending on various social and economic factors using the econometric log-linear regression model, based on the surveys in the analyses. Several articles [30–32] have studied the dependence of energy consumption from renewable sources on the basis of estimated econometric regression models. These studies have involved different countries and the use of different models in the analyses carried out. Publication [30] analyses the ongoing changes in energy consumption (total and from renewable sources) in 10 EU countries from the point of view of factors determining the functioning of the circular economy using the Econometric Panel model. The paper [31] presents a study of factors that influence the consumption of energy from renewable sources in European countries with the highest goals of sustainable development such as Denmark, Norway, Finland, France, and Sweden and Visegrad countries such as Poland, the Czech Republic, Hungary, the Slovak Republic, and Ukraine as a candidate country for EU membership using the Panel Data Regression model and the Generalised Method of Moments (GMM) method. On the other hand, the publication [32] examined the factors that influenced the increase in the share of renewable energy consumption in total energy consumption. GDP per capita was shown to have the greatest impact. Scenarios for the share of RES for 2020 in the EU-28 countries were presented using Econometric Panel models and cluster analysis. Several other exemplary publications, for example in [33], contain an economic and spatial analysis of the determinants of electricity consumption in 34 European countries (including 26 EU countries) using the panel data regression model and the spatial Durbin model (SDM). In the work [34], a study was carried out on the relationship between energy production and many factors that influence it. The factors include energy import, energy prices, and energy productivity and efficiency. The study was carried out in 37 European countries using the following models. Linear and non-linear econometric models and the generalised method of moments (GMM). Finally, the publication [35] 'analyses the interdependence between energy consumption and the country's economic growth (GDP) and the individual credit ratio as a determinant of financial development' in Azerbaijan using the Vector Error Correction Model (VECM).

A separate group of publications are works that present in addition to estimated models describing the studied dependences of energy consumption or production (especially from renewable sources, but not only) on many different factors shaping it as well as its use to forecast in a longer or shorter time horizon. The paper [36] presents a forecast for 2017–2020 for the share of renewable energy consumption in the final energy consumption using the estimated ARIMA autoregressive model in the 28 EU countries. On the other hand, the paper [37] features a forecast of the share of energy from renewable sources in the total energy consumption in the transport sector, as well as the energy used for lighting and heating purposes, using the linear multiple regression model. The paper [38] presents a forecast of electricity consumption in various sectors of the Polish economy for five-year periods up to 2040 using the long- and short-term memory (LSTM) model and artificial neural networks (ANN). Similarly, work [39] contains a forecast for energy production by 2025 from various types of renewable sources and from biofuels using artificial neural networks, multilayer perceptron (MLP). Publication [40] presents 'forecasts for the share of energy from renewable sources and the consumption of energy from renewable sources' in the Czech Republic and Slovakia for 2018–2020 using ARIMA autoregressive models. The articles [41–43] present 'forecasting models and a forecast of energy consumption in households in the residential sector' for scenarios for 2017–2030 in four selected European countries (Germany, Italy, Spain, and Lithuania) using a multiple regression econometric model [41], and a forecast for the variability of electricity consumption in households during the day in Palermo, Italy, and Sicily, taking into account the impact of microclimatic and weather factors and using neural networks (Elman Neural Network) [42].

Another publication [44] presents a long-term forecast until 2020 for the Baltic countries (Latvia, Lithuania, and Estonia) for the demand for energy in various sectors of the economy, in particular in the production and transport sectors. 'An analysis of long-term relationships between economic growth and energy demand was carried out using the author's own proposed econometric model'. On the other hand, in the work [45], an analysis of the interdependence between the production of energy from renewable sources, the total production of energy (from fossil and renewable sources), and the final consumption of energy was carried out in the EU-28 countries using a vector econometric model of autoregression. Vector autoregression (VAR) and a long-term forecast were presented using estimated models until 2080.

A thorough analysis of the publication of this section in the field of forecasting energy production and use shows that this is an up-to-date and important issue that should be addressed. This paper is an attempt to synthesise many approaches of different authors and combine in one article the description and forecasting of energy consumption in households, both in terms of energy from fossil and renewable sources. The previous papers were based mainly on the data from previous years, so their forecast results may already be outdated. In addition, the approach presented in this article uses not only point forecasts (which can and are subject to error) but also more flexible interval forecasts. No such approach was noted in other articles examined.

A detailed analysis of the literature discussed is presented in Table 3.

Table 3. Detailed analysis of the literature.

Authors Publication Date Reference	Region, Country (Time Range of Research)	Research Methods Applied
Alam and Murad 2020 [23]	25 OECD countries (1970–2012)	Panel Cointegration Autoregressive Distributed Lag Model (ARDL)
Anghelache et al., 2023 [45]	EU-28 countries (2000–2020) Long-term forecasts for 2080	Vector Autoregression Model (VAR)
Armeanu et al., 2017 [22]	EU-28 countries (2003–2014)	Panel Vector Error Correction (PVECM) Model, Granger Causality Test
Batrancea and Tulai 2022 [34]	37 European countries (2011–2021)	Linear And Non-Linear Econometric Models Generalised Method Of Moments (GMM)
Becalli et al., 2008 [42]	Italy (2002–2003)	Neural Networks Elman Neural Network (ANN)
Bianco et al. [41]	Four European countries: Germany, Italy, Spain, Lithuania (2000–2016, forecasts for scenarios for years 2017–2030)	Multiple Regression Econometric Model
Bissiri et al., 2019 [26]	The UK and Germany, (1991–2015)	Log-Linear Model Multiple Regression Model Analysis Of Elasticity Coefficients
Brodny et al. [39]	Poland (1990–2018, forecasts until 2025)	Artificial Neural Networks (ANN) (Multi-Layer Perceptron—MLP)
Brożyna et al. [40]	The Czech Republic, Slovakia (1990–2017, forecasts for 2018–2020)	ARIMA Models
Bueno et al., 2020 [28]	Spain (2013–2017)	Multiple Regression Econometric Model (Log-Linear)
Busu 2019 [19]	EU-27 countries (2008–2017)	Suggested Own Econometric Model
Busu 2020 [20]	EU-28 countries (2004–2017)	Autoregressive Distributed Lag Model (ARDL)
Flores-Chamba et al., 2019 [33]	34 European countries, including 26 from EU (2000–2016)	Panel Data, Regression Models Generalised Least Squares (GLS) Spatial Durbin Model (SDM)
Khan and Osińska 2022 [30]	10 countries: Estonia, Greece, Italy, Latvia, Lithuania, Norway, Poland, Slovenia, Spain, and The UK (2010–2019).	Econometric Panel Model
Krkošková 2021 [13]	V4 countries: Poland, Slovakia, The Czech Republic, Hungary (2005–2019)	Autoregressive Model Type Vector Error Correction Model (VECM)
Li and Leung 2021 [24]	Seven OECD countries: Germany, Italy, The Netherlands, Poland, Spain, Turkey, The UK (1985–2018)	Panel Vector Error Correction Model (PVECM) Granger Causality Test
Makuteniene et al., 2023 [17]	Baltic countries: Lithuania, Latvia, Estonia (1995–2019)	Non-Linear Autoregressive Distributed Lag (NARDL) Model
Manowska [38]	Poland (1990–2017, five-year period forecasts until 2040)	Artificial Neural Networks Long-Short-Term Memory (LSTM)
Mehedintu et al. [36]	EU-28 countries (1995–2016, forecasts for 2017–2020)	ARIMA Autoregressive Models
Mehedintu et al. [37]	EU countries vs. Romania (2004–2019, forecasts for the 2030 horizon)	Multiple Regression Econometric Model
Miskinis et al. [44]	Three Baltic States: Estonia, Lithuania, Latvia (2000–2016, forecasts for a time horizon of four years until 2020)	Suggested Own Econometric Model

Table 3. *Cont.*

Authors Publication Date Reference	Region, Country (Time Range of Research)	Research Methods Applied
Mukhtarov et al., 2018 [35]	Azerbaijan (1992–2015)	Vector Error Correction Model (VECM)
Piłatowska and Geise 2021 [18]	Three European countries: France, Spain, Sweden (1972–1999)	Vector Autoregression Model (VAR) Granger Causality Test
Polcyn et al., 2018 [31]	Countries with the highest sustainable development goals: Denmark, Norway, Finland, France, and Sweden Visegrad Countries: Poland, The Czech Republic, Hungary, The Slovak Republic, and potential candidate to EU, i.e., Ukraine (2000–2018)	Panel Data Regression Generalised Method Of Moments (GMM)
Romero-Jordan et al., 2014 [27]	Spain (1998–2009)	Panel Data Model (Partial Adjustment Model)
Shojaee and Seyedin 2021 [14]	Countries of Central and Eastern Europe: 11 countries (1996–2020)	Experimental Design With Response Surface Method (RSM) Panel Data Regression, Correlation Analysis
Simionescu et al., 2020 [32]	EU-28 countries (2007–2017)	Panel Data Models Cluster Analysis
Soava et al., 2021 [15]	Romania (2007–2020)	Multi-Linear Regression
Topolewski 2021 [16]	34 European countries including EU-27 (2008–2019)	Dynamic Panel Regression (DPR) Models
Wiesmann et al., 2011 [29]	Portugal 2001, 2005–2006	Log-Linear Econometric Models Survey
Zhao and Wang 2015 [21]	China (1980–2012)	Cointegration Test Granger Causality Test

3. Materials and Methods

The econometric model presents relationships that occur in economic processes taking into account only the most important factors. The purpose of regression analysis is to study the relationships between multiple independent (explanatory) variables and a dependent (explained) variable, which must be numerical. The estimated regression econometric model makes it possible to answer the question of which values best describe the phenomenon in the study. After selecting the appropriate set of diagnostic variables, the structural parameters of the model are estimated. Next, the quality of the fit of the model to the data is checked, usually adjusted with the coefficient of determination R_a^2, which indicates to what extent the model is correctly fitted. The next step should be the verification of the model, i.e., checking the basic assumptions regarding the distribution of model residuals: normality, symmetry, randomness, variance constancy, and lack of autocorrelation.

The generalised multiple regression model used in the research, which describes the variability of the phenomenon studied over time, is of the following form [46]:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_1 X_{2t} + \ldots + \beta_p X_{pt} + \varepsilon_t \tag{1}$$

In order to estimate the predicted future values for the independent variables in the multiple regression model, regression models for the linear trend of the following form were used:

$$X_{it} = \beta_0 + \beta_1 t + \varepsilon_{it} \tag{2}$$

In some cases, for independent variables (where a better fit was observed) exponential smoothing models with a linear trend or with a fading trend were used. The exponential smoothing model with a linear trend (Holt linear trend model) and the model with a fading trend are described by the relationships [47]:

Holt linear trend model

$$\begin{gathered} S_t = \alpha X_t + (1-\alpha)(S_{t-1} + T_{t-1}) \\ T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)T_{t-1} \\ \hat{X}_t(m) = S_t + mT_t \end{gathered} \tag{3}$$

Damped Trend Model

$$\begin{gathered} S_t = \alpha X_t + (1-\alpha)(S_{t-1} + \varphi T_{t-1}) \\ T_t = \gamma(S_t - S_{t-1}) + (1-\gamma)\varphi T_{t-1} \\ \hat{X}_t(m) = S_t + \sum_{i=1}^{m} \varphi^i T_t \end{gathered} \quad (4)$$

where:

α—smoothing parameter for the level of the series $(0 \leq \alpha \leq 1)$,

γ—smoothing parameter for trend $(0 \leq \gamma \leq 1)$,

φ—damped trend modification parameter $(0 < \varphi < 1)$,

X_t—observed value of the time series in period t,

S_t—smoothed level of the series, computed after X_t is observed,

T_t—smoothed trend at the end of period t,

$\hat{X}_t(m)$—forecast for m period ahead from origin t.

The adjustment quality of the estimated regression models to the data and predictive models for independent variables (ex-post model performance) was measured by means of known measures of prediction quality. For linear regression models, the adjusted coefficient of multiple determination was used.

(The adjusted coefficient of multiple determination) defined as follows [46]:

$$R_a^2 = 1 - \frac{(n-1)}{(n-p-1)} \frac{SSE}{SSTO} \quad (5)$$

where:

$SSE = \sum_{t=1}^{n} \varepsilon_t^2 = \sum_{t=1}^{n} \left(\hat{Y}_t - Y_t\right)^2$—sum of squares error;

$SSTO = \sum_{t=1}^{n} \left(Y_t - \overline{Y_t}\right)^2$—Sum of squares total;

$\overline{Y}_t$—mean value of dependent variable Y_t.

In addition, measures of predictive quality of the models used in time series analysis were used, such as [48]:

- MSSE (mean sum of squares error) calculated as:

$$\begin{gathered} MSSE_Y = \frac{1}{n} \sum_{t=1}^{n} \varepsilon_t^2 = \frac{1}{n} \sum_{t=1}^{n} \left(\hat{Y}_t - Y_t\right)^2 \\ MSSE_{X_{it}} = \frac{1}{n} \sum_{t=1}^{n} \varepsilon_{it}^2 = \frac{1}{n} \sum_{t=1}^{n} \left(\hat{X}_{it} - X_{it}\right)^2 \end{gathered} \quad (6)$$

- MAE (mean absolute error) calculated as:

$$\begin{gathered} MAE_Y = \frac{1}{n} \sum_{t=1}^{n} |\varepsilon_t| = \frac{1}{n} \sum_{t=1}^{n} \left|\hat{Y}_t - Y_t\right| \\ MAE_{X_{it}} = \frac{1}{n} \sum_{t=1}^{n} |\varepsilon_{it}| = \frac{1}{n} \sum_{t=1}^{n} \left|\hat{X}_{it} - X_{it}\right| \end{gathered} \quad (7)$$

- MAPE (mean absolute percentage error) calculated as:

$$\begin{gathered} MAPE_Y = \frac{1}{n} \sum_{t=1}^{n} \left|100 \times \frac{Y_t - \hat{Y}_t}{Y_t}\right| \\ MAPE_{X_{it}} = \frac{1}{n} \sum_{t=1}^{n} \left|100 \times \frac{X_{it} - \hat{X}_{it}}{X_{it}}\right| \end{gathered} \quad (8)$$

where:

$\hat{Y}_t$, $\hat{X}_{it}$—predicted values for the dependent variable Y_t and the independent variable X_{it} _it based on the model;

Y_t, X_{it}—actual values for the dependent variable and the independent variables.

Statistical tests known from the literature were used to study the properties of the regression models' residuals. In the study of the normality of the residuals, the very popular and frequently used in practice Goodness-of-Fit χ^2 test, and the less frequently used D'Agostino–Pearson test based on the analysis of skewness and kurtosis measures were used [49]. The series test was applied to test the randomness of the residuals, and the symmetry test based on Student's t-statistics was used to test the symmetry of the residuals. The following tests were applied in the variance heteroscedasticity testing by Breusch-Pagan [50] and White test [51]. The Durbin–Watson test [52] was used to test the lack of autocorrelation of model residuals.

Confidence level $(1-\alpha)$ prediction limits for new observations. The $(1-\alpha)$ prediction limits for the new observation $Y_{h(new)}$ corresponding to X_h, and following are the specified values of the X variables [46]:

$$\begin{aligned} Y_{h(new)}{}^{Lo}_{(1-\alpha)} &= \hat{Y}_h - t\left(1-\tfrac{\alpha}{2}; n-p-1\right)s\{pred\} \\ Y_{h(new)}{}^{Hi}_{(1-\alpha)} &= \hat{Y}_h + t\left(1-\tfrac{\alpha}{2}; n-p-1\right)s\{pred\} \end{aligned} \quad (9)$$

where:

$s^2\{pred\} = MSE\left(1 + X_h^T\left(X^TX\right)^{-1}X_h\right)$,
MSE—mean square error (residual mean square),
n—number of observations for the linear multiple regression model,
p—number of independent variables without intercept,
t—value of the t-Student distribution statistics.

4. Results

The purpose of the conducted analyses was to construct two econometric models that would describe energy consumption in households in the European Union countries. One of the models was concerned with the consumption of energy from fossil sources (M1) and the other with the consumption of energy from renewable sources and biofuels (M2). The research was carried out on the basis of data obtained from the Eurostat database. It covered the period from 1995 to 2021 (26 observations). Estimated models were used in the econometric forecast of energy consumption in households.

Initially, more than 80 indicators were selected that described energy consumption from various sources and economic characteristics for model construction. After the analysis of the coefficient of variation and the analysis of correlations, a dozen or so indices were qualified for the model. They were considered as potential variables describing both analysed regression models. The final variables that entered both models were always statistically significant and affected the modelled relationships in a relevant way. The stepwise regression method and the Statistica 13 program were used to estimate the final models.

The final set of indicators was characterised by calculating basic descriptive statistics and presenting their trends on line charts.

4.1. Presentation of the Collected Material

The list of indicators that were used to construct econometric models of energy consumption in households in the European Union countries is presented below along with their symbols, which are later used in the mathematical forms of the models.

Y_{1t}—Final energy consumption—households (energy use)—solid fossil fuels (ktoe, thousand tonnes of oil equivalent) [53],

Y_{2t}—Final energy consumption—households (energy use)—renewables and biofuels, (ktoe) [53],

X_{1t}—Final consumption expenditure—households (Euro per capita) [54],
X_{2t}—Average full-time adjusted salary per employee (Euro) [55],
X_{3t}—Imported energy—lignite (ktoe) [53],
X_{4t}—Primary energy production—Wind (ktoe) [53],

X_{5t}—Primary energy production—nuclear heat (ktoe) [53].

Table 4 presents the basic descriptive statistics of the variables used in the research. The first two indicators are dependent variables. The trends of the time series are presented in Figure 2. It shows that the use of energy from fossil sources is characterised by a downward trend, and each year less and less energy from these sources is used in households in EU countries. Consumption dropped from 1649.5 ktoe to 6435.4 ktoe. The coefficient of variation of almost 25% shows the diversification of fossil source energy consumption in the analysed years. The consumption of energy from renewable sources shows exactly the opposite trend—an upward trend. Growth is very aggressive from 26,843.2 ktoe to 55,607 ktoe.

Table 4. Basic descriptive statistics of selected variables.

	$\overline{X}_G$	M_e	Min	Max	σ	V_z	S	K
$\mathbf{Y_{1t}}$	9288.1	8819.1	6435.4	16,490.5	2372.9	24.9	1.7	3.1
$\mathbf{Y_{2t}}$	39,450.0	43,234.9	26,843.2	55,606.7	8814.4	21.8	−0.1	−1.5
$\mathbf{X_{1t}}$	12,324.8	13,110.0	8140.0	16,210.0	2480.7	19.7	−0.3	−1.1
$\mathbf{X_{2t}}$	26,825.0	27,010.0	21,902.0	33,511.0	3408.3	12.6	0.2	−1.0
$\mathbf{X_{3t}}$	623.3	520.2	189.6	2373.7	568.6	74.0	1.6	1.8
$\mathbf{X_{4t}}$	6455.1	9736.4	316.2	34,204.5	11,178.5	89.0	0.6	−0.9
$\mathbf{X_{5t}}$	213,345.7	215,220.6	175,176.1	239,962.4	16,510.5	7.7	−0.4	−0.3

$\overline{X}_G$—geometric mean, M_e—median, σ—standard deviation, V_z—variation coefficient, S—skewness, K—kurtosis.

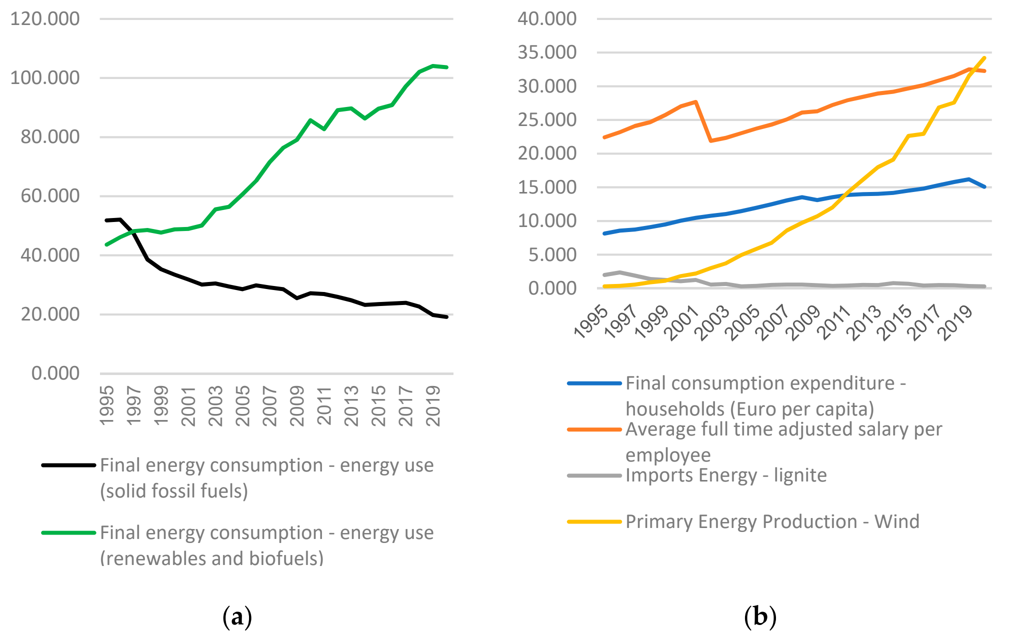

Figure 2. (**a**) Final energy consumption—households (energy use)—solid fossil fuels and renewables and biofuels; (**b**) Final consumption expenditure, average full time adjusted salary per employee, imported energy—lignite and primary energy production—wind.

The variable X_1, i.e., the final consumption expenditure–households (Euro per capita) was added to the M1 and M2 models. It entered the M1 model as the first and most important, while in the M2 model, it appears at the end but also describes the consumption of energy from renewable sources in households in a significant way. Figure 2 shows that the trend is upward, expenses are growing steadily, and in 2020, there was a slight decrease, which could have been caused by the COVID-19 pandemic, but in 2021, expenses were increasing again.

Another variable that entered the M1 model is the average adjusted full-time salary per employee (Euro) (X_2). The time series shows that the trend is also increasing. In 2020, there was a slight decrease, but in 2021, the indicator entered the path of growth again.

X_3—is imported energy—lignite [ktoe], which is characterised by a decrease over time, from 2373.7 ktoe to 189.6 ktoe.

Another feature that describes energy consumption in households is primary energy production—wind [ktoe], (X_4) it is characterised by the highest increase in the analysed period. From the level of 316.2 ktoe, it increases to the level of 32,204.5 ktoe. The coefficient of variation is at the level of 89%, which means a very large diversification of wind energy production in the period analysed. Today, where the emphasis is put on the use of renewable energy sources, wind farms are developing very dynamically, both on land and on sea.

The last indicator that entered the investigation was primary energy production, nuclear heat [ktoe] (X_5). It shows the greatest stability—the coefficient of variation was only 7.7%, which means that the production of nuclear energy in the analysed period is homogeneous. However, there is a trend in the series. Production increased from 1995 until 2004, followed by a decrease in production until 2020, and only in 2021 did production increase again. The order of magnitude is completely different from in other sources of energy production; therefore, the data are presented in a separate graph (Figure 3). In the case of nuclear energy production, the average is 213,345.7 ktoe.

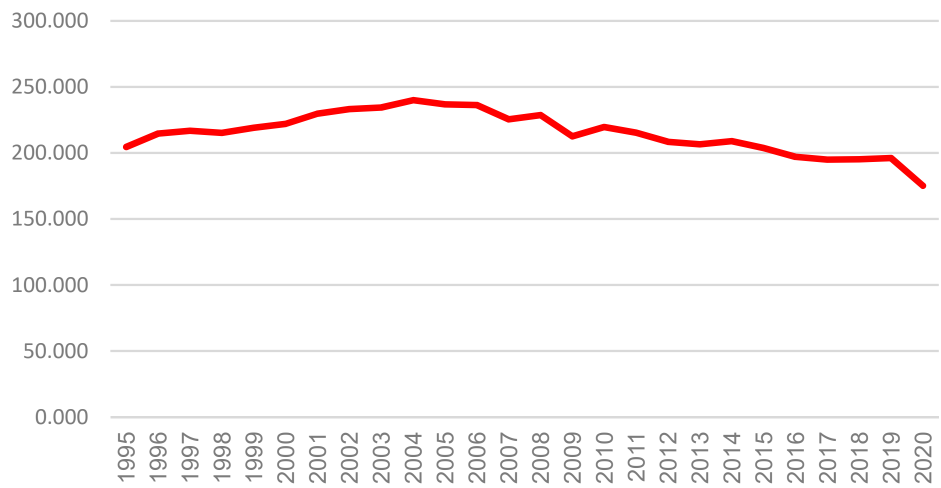

Figure 3. Primary energy production—nuclear heat [ktoe].

4.2. Construction of Econometric Models

4.2.1. Construction of the Model That Defines the Final Energy Consumption in Households (Energy Use) from Solid Fossil Fuels (Y_{t1})

Three variables have entered the model that affect (determine) the final consumption of energy from fossil fuels in households. These are final consumption expenditure–households (Euro per capita) (X_1), average full-time adjusted salary per employee (X_2), and import energy—lignite (X_3). The model fits the data in 77%, as evidenced by the coefficient of determination ($R_a^2 = 0.77$). The form of the model, along with the estimation errors, is presented in dependencies (10).

$$\begin{array}{cccc} \hat{Y}_{1t} = 8304.1 & +\ 0.994X_{1t} & -\ 0.569X_{2t} & +\ 5.329X_{3t} \\ (2423.8) & (0.29) & (0.15) & (0.82) \\ p = 0.0024 & p = 0.0027 & p = 0.0008 & p = 0.0000 \end{array} \quad (10)$$

After the model development, it was thoroughly verified to check its correctness and possibilities of its practical interpretation. A correctly estimated model that can be used for further analysis, including forecasting, should have many desirable (required) properties. One of the most important assumptions of a well-estimated model is the assumption of normality of the distribution for residuals. The residuals should also be characterised by randomness, symmetry, constancy of variance, and lack of autocorrelation.

- Checking the assumption about the normal distribution of residuals

The null hypothesis in this case is that the distribution of residuals is normally distributed. The analysis of the conducted Chi-square test shows that the value of the test statistic $\chi^2_{stat} = 0.926$ and with the corrected number of degrees of freedom (df = 1) the test probability is $p = 0.336$. Since $p > \alpha = 0.05$, then there is no reason to reject the H_0 hypothesis that the distribution of residuals is normal. Fitting the distribution of residuals to the normal distribution is shown in the figure (Figure 4).

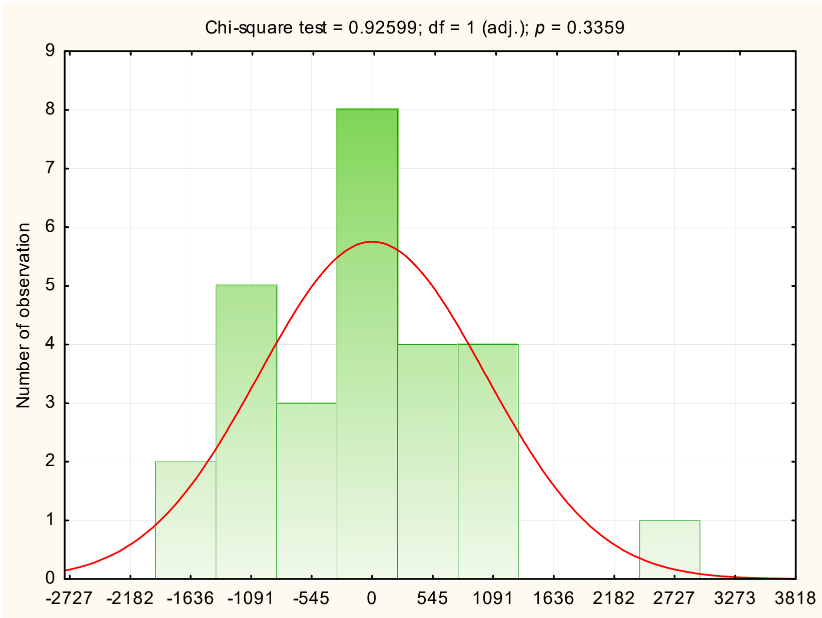

Figure 4. Fitting the normal distribution of residuals of the M1 model.

A similar result is obtained on the basis of the d'Agostino–Pearson normality test. The value of the test statistic is $DA_{stat} = 2.049$, which has an asymptotic Chi-square distribution with (df = 2) degrees of freedom. The test probability is therefore p = 0.359, so there is also no reason to reject the hypothesis that the residuals are normally distributed.

- Checking the assumption about the symmetry of the distribution of residuals

If the assumption about the symmetry of the distribution of residuals is checked, the null hypothesis says that the distribution of residuals is symmetric: $\left[\frac{m}{n} = \frac{1}{2}\right]$, where m is the number of positive residuals and n is the number of all residuals. The value of the test statistic t_{emp} = 0.96, while the critical value read from the tables t_α = 2.056, i.e., $t_{emp} < t_\alpha$; therefore, there is no reason to reject the null hypothesis and the residuals have a symmetrical distribution.

- Checking the assumption about the randomness of residuals

The null hypothesis states that the distribution of residuals is random. The 'Stevens' series test or the 'Wald-Wolfowitz' series test, which are nonparametric tests of sample randomness, are used to check. From the residuals, a base sequence is formed, the observations are ordered in ascending order, and the median is determined. In the basic sequence, the symbols a and b denote values that differ from the median: less than the median as 'a' and greater than the median as 'b'. Values equal to the median are skipped. When analysing the arrangement of symbols in the basic string, the number of series denoted k is counted. It is the statistic value obtained from the sample. The critical area of the test is two-sided. The values of k_1 and k_2 are read from the tables; if k is less than or equal to

k_1 or k is greater than or equal to k_2, the hypothesis of randomness should be rejected. In the analysed case k = 11, k_1 = 8, k_2 = 19, $k_1 < k < k_2$, so there is no reason to reject H_0, the residuals have a random distribution.

- Checking the assumption about the constancy of residual variance

The null hypothesis is that the residuals of the model have constant variance (homoscedastic) $\mathrm{H}_0 : \sigma_i^2 = \sigma^2 =$ constant for all observations $i = 1, \ldots, n$. The test statistic is: $\mathrm{LM} = \mathrm{n}R^2_{new}$, gdzie R^2_{new} where R^2_{new}—R-square of the new regression model that used the squared residuals as the response values. This statistic has a limiting Chi-square distribution with the number of degrees of freedom ($df = k$), where k is the number of independent variables in the regression model. The calculated value of the test statistic for our model is $\mathrm{LM_{stat}} = 0.897$, so for k = 3 degrees of freedom, the value of the test probability is p = 0.826. Since $p > \alpha = 0.05$, there is no reason to reject the hypothesis about the constancy of variance of model residuals. A similar result is obtained using the White test, for which the value of the test statistic is 0.445 and the test probability p = 0.8. Therefore, at the significance level of α = 0.05, there are also no grounds to reject the hypothesis of constant variance of the residuals of the model.

- Checking the assumption of no autocorrelation for residuals

Since the data in the regression model are time series, the hypothesis that the residuals do not have significant positive (negative) autocorrelations was also tested. The value of the test statistic for the Durbin–Watson test $d_{stat} = 1.137$, which with the critical values of lower $d_L = 1.143$ and upper $d_U = 1.652$ for the significance level α = 0.05, suggests that there are rather significant positive residual autocorrelations.

4.2.2. Construction of the Model That Defines the Final Energy Consumption in Households (Energy Use) from Renewable and Biofuels (Y_{t2})

Three variables have also been added to the model, which affect (determine) the final consumption of energy from renewable biofuel energy sources in households. These are primary energy production, wind (X_4), primary energy production, nuclear heat (X_5), and final consumption expenditure, households (Euro per capita) (X_1). The model fits the data at 95%, as evidenced by the coefficient of determination ($R^2_a = 0.95$). The form of the model along with the estimation errors is presented in dependencies (11):

$$\begin{array}{cccc} \hat{Y}_{2t} = 39,803.087 & -\ 0.583X_{4t} & -\ 0.249X_{5t} & +\ 4.861X_{1t} \\ (10,450.1) & (0.22) & (0.07) & (0.70) \\ p = 0.0009 & p = 0.0137 & p = 0.0012 & p = 0.0000 \end{array} \quad (11)$$

The residuals of the estimated model were also thoroughly verified whether they meet the required assumptions about their properties.

- Checking the assumption about the normal distribution of residuals

The analysis of the Chi-square test shows that the value of the test statistic $\chi^2_{stat} = 0.412$, and with the corrected number of degrees of freedom (df = 1), the test probability is p = 0.673. Since $p > \alpha = 0.05$, there is no reason to reject the hypothesis that the residual distribution is normal. The fit of the distribution is shown in Figure 5.

- Checking the assumption about the symmetry of the distribution of residuals If the assumption about the symmetry of the distribution of residuals is checked, the null hypothesis says that the distribution of residuals is symmetric: $\left[\frac{\mathrm{m}}{\mathrm{n}} = \frac{1}{2}\right]$, where m is the number of positive residuals and n is the number of all residuals. The value of the test statistic t_{emp}= 0.18, while the critical value read from the tables t_α = 2.056, i.e., $t_{emp} < t_\alpha$; therefore, there is no reason to reject the null hypothesis and the residuals have a symmetrical distribution.
- Checking the assumption about the randomness of the distribution of residuals The null hypothesis states that the distribution of residuals is random. In the analysed case,

$k = 12$, $k_1 = 9$, $k_2 = 19$, $k_1 < k < k_2$, so there is no reason to reject H_0, and the residuals have a random distribution.

- Checking the assumption of constancy of residual variance The calculated value of the test statistic for the Breusch–Pagan test in this case is $LM_{\_stat} = 4.6$, so for $k = 3$ degrees of freedom, the test probability value is $p = 0.203$. Since $p > \alpha = 0.05$, there is no reason to reject the hypothesis about the constancy of variance of model residuals. A similar result is obtained using the White test, for which the value of the test statistic is 1.18, and the test probability $p = 0.554$. Therefore, at the significance level of $\alpha = 0.05$, there are also no grounds to reject the hypothesis of constant variance of the residuals of the model.
- Checking the assumption of no autocorrelation for residuals

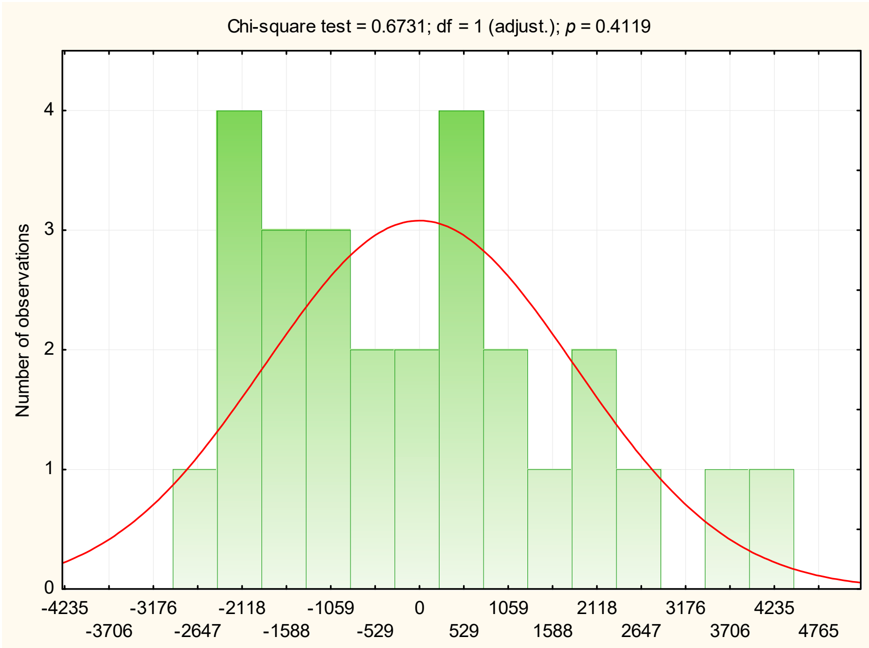

Figure 5. Fitting the normal distribution of residuals of the M2 models.

Since the data in the regression model are time series, the hypothesis that the residuals do not have significant positive (negative) autocorrelations was also tested. The value of the test statistic for the Durbin–Watson test $d_{stat} = 1.729$, which with the critical values of lower $d_L = 1.143$ and upper $d_U = 1.652$ for the significance level $\alpha = 0.05$ implies that there are no significant positive autocorrelations of residuals (no autocorrelation of residuals).

4.2.3. Forecasting the Amount of Energy Consumption in Households Based on Estimated Models

To construct a forecast based on the estimated models, the future values of the independent variables that have entered the model must be known. Therefore, first, forecasts were made for individual independent variables by selecting adequate forecasting methods based on time series. For the forecast of X_{1t}—final consumption expenditure (households) and X_{2t}—average full-time adjusted salary per employee, a linear regression model was used, while for the forecast of X_{3t}—imported energy—lignite, X_{4t}—primary energy production—wind, and X_{5t}—primary energy production—nuclear heat, exponential smoothing models with appropriately adjusted parameters were used. The results of fitting the forecasting models to the data and the estimated errors of the 'ex-post' forecasts (for previous known observations) and the errors of the 'ex-ante' forecasts (for future unknown observations) using the quality measures of the estimated models (Formula (5)–(8)) are presented in the table (Table 5).

Table 5. Measures of the fit quality of forecasting models for independent variables used in household energy consumption models.

The Independent Variable in the Model (Parameters of the Forecasting Model)	Forecast Errors	
	Ex-Post	**Ex-Ante (for t = 27, 2021) PE [%]**
X_{1t}—Final consumption expenditure (households) Linear regression model $X_{1,t} = 8236.3 + 311.2t$	$R_a^2 = 0.97$ MAE = 315.5 MSSE = 180,424.6 MAPE = 2.6 [%]	PE = −2.64 [%]
X_{2t}—Average full-time adjusted salary per employee Linear regression model $X_{2t} = 17,304.7 + 596.6t$	$R_a^2 = 0.99$ MAE = 242.5 MSSE = 80,443.7 MAPE = 0.88 [%]	PE = 0.29 [%]
X_{3t}—Imported energy—lignite Holt's linear exponential smoothing model Formula (3) Model parameters: $\alpha = 0.8; \gamma = 0$	MAE = 173.3 MSSE = 53,579.1 MAPE = 25.4 [%]	PE = −17.9 [%]
X_{4t}—Primary energy production—wind Exponential smoothing model with fading trend pattern (4) Model parameters: $\alpha = 0.7; \gamma = 0.1; \varphi = 0.9$	MAE = 1262.5 MSSE = 2,457,476.3 MAPE = 42.45 [%]	PE = −3.6 [%]
X_{5t}—Primary energy production—nuclear heat Exponential smoothing model with fading trend pattern (4) Model parameters: $\alpha = 0.2; \gamma = 0.7; \varphi = 0.9$	MAE = 3966.6 MSSE = 34,077,706.1 MAPE = 1.96 [%]	PE = 0.97 [%]

By substituting the obtained forecast values for the independent variables to the estimated forecasting models, the forecast values for the dependent variables $\hat{Y}_{1t}$—Final energy consumption in households (energy use)—solid fossil fuels and $\hat{Y}_{2t}$—Final energy consumption in households (energy use)—renewables and biofuels were obtained. Basic errors of ex-post and ex-ante forecasts were also estimated (Formulas (5)–(8)) for the forecasts performed, which are presented in the table (Table 6).

Table 6. Quality of fit measures for linear econometric models used to forecast energy consumption in households for energy purposes.

Dependent Variable (in a Linear Regression Model)	Forecast Errors	
	Ex-Post	**Ex-Ante t = 27 (2021) PE [%]**
$\hat{Y}_{1t}$—Final energy consumption in households (energy use)—solid fossil fuels	$R_a^2 = 0.77$ MAE = 814.5 MSSE = 1,043,003.2 MAPE = 8.8 [%]	for t = 27 (2021) Percentage error PE = 1.13 [%]
$\hat{Y}_{2t}$—Final energy consumption in households (energy use)—renewables and biofuels	$R_a^2 = 0.95$ MAE = 1474.1 MSSE = 3,161,408.2 MAPE = 3.8 [%]	for t = 27 (2021) Percentage error PE = 5.2 [%]

Table 7 presents the final values of point forecasts $\hat{Y}_{1t}$ and $\hat{Y}_{2t}$ and interval ones $[\hat{Y}^{Lo}_{t95\%}, \hat{Y}^{Hi}_{t95\%}]$ (Formula (9)) for the expected energy consumption for energy purposes in households from fossil sources Y_{1t} and renewable ones Y_{2t}.

Table 7. Point and interval forecasts for dependent variables of the models.

(Year) t	Y_{1t}	$\hat{Y}_{1t}$	$\hat{Y}^{Lo}_{1t95\%}$	$\hat{Y}^{Hi}_{1t95\%}$	$Y_{2,t}$	$\hat{Y}_{2,t}$	$\hat{Y}^{Lo}_{2t95\%}$	$\hat{Y}^{Hi}_{2t95\%}$
(2021) 27	6435.4	6362.4	3807.3	8917.4	55,606.7	52,686.5	48,230.1	57,143.0
(2022) 28		6630.9	4065.5	9196.4		56,274.0	51,789.6	60,758.4
(2023) 29		6237.6	3634.6	8840.7		58,002.4	53,452.9	62,551.9

The graph (Figure 6) shows the forecast for the consumption of energy from fossil sources in households. An expected trend (Table 5) trend of a further decrease in the use of fossil energy in households (with the detriment of the use of traditional energy) can be observed (departing from the use of traditional energy). For 2021, the forecast was 6362 (ktoe), where the actual value was 6435 (ktoe). Therefore, the forecast underestimated the actual value expressed as a percentage forecast error (PE (%)) by approximately 1.13 (%). Based on the constructed M1 econometric model, a slight increase is expected to reach the level of 6630 (ktoe) in 2022 is forecast for Y_{1t} variable, followed by a significant decrease to the level of 6237 (ktoe) in 2023 and potentially subsequent years, if this downward trend continues.

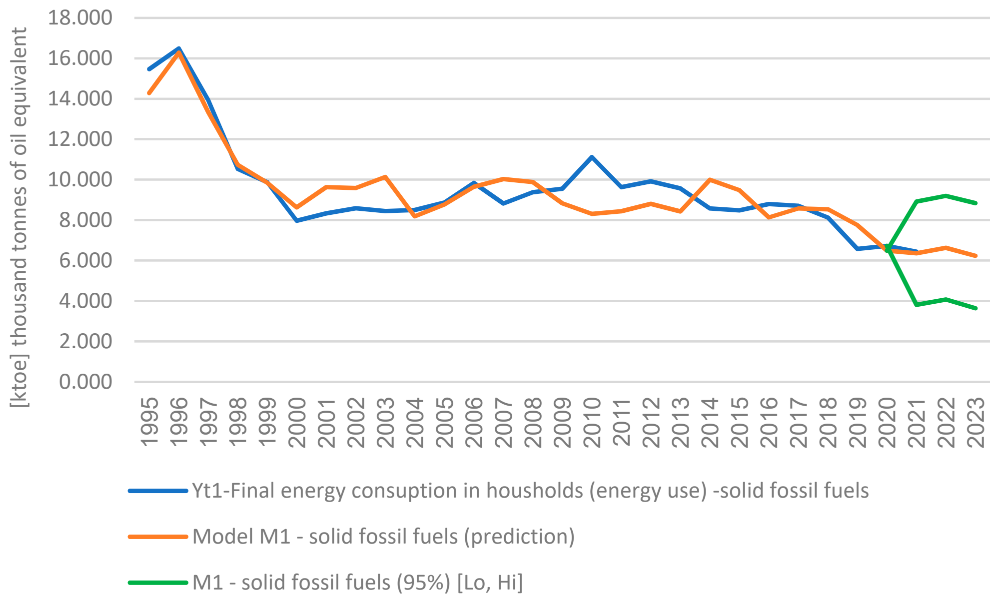

Figure 6. Forecast of energy consumption from traditional fossil sources in households in EU countries.

The graph (Figure 7) shows the forecast for the consumption of energy from renewable sources and biofuels in households. An expected trend (Table 5) trend of a further systematic increase in the use of this type of energy in households (environmentally friendly energy) can be observed. For 2021, the forecast was 52,686 (ktoe), where the actual value of this variable was 55,606 (ktoe) (more than 8.5 times more than the energy from traditional fossil sources). In this case, the forecast also underestimated the actual value expressed as a percentage forecast error (PE (%)) by about 5.2 (%). Based on the constructed M2 econometric model, a successive increase in its value is forecast to be at the level of 56,274 (ktoe) in 2022 and at the level of 58,002 (ktoe) in 2023 and possibly in subsequent years, if, of course, this upward trend continues. It should be noted that the actual values of the Y_{2t} variable are within the limits of its prediction (95%).

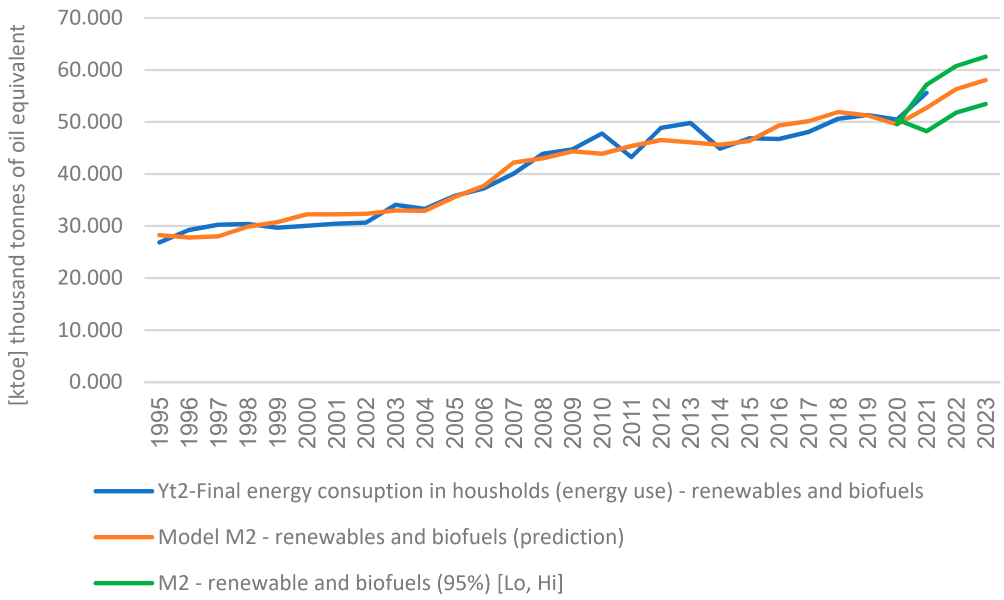

Figure 7. Forecast of the consumption of energy from renewable sources and biofuels in households in EU countries.

5. Discussion

Today, electricity consumption is a major problem. Especially households are struggling with the increasing consumption of electricity and thus with the costs that this consumption generates. We are surrounded on all sides by devices that consume electricity (because without it their operation is not possible). Therefore, the paper deals with the subject of analysing electricity consumption in households and checking what sources it comes from and what the prospects are for its consumption. It is well known that consumers try to save energy by installing energy-saving devices in their homes, which will help reduce energy consumption and related costs, even if only in a small way. Studies show that energy consumption contributes to long-term GDP growth [14,15]. In [21], an analysis of the interdependence between energy consumption and factors that characterise the level of urbanisation and economic growth (GDP) was carried out. There is a two-way reciprocal causality between energy consumption and economic growth and that urbanisation causes an increase in energy consumption, and economic development contributes to more urbanisation. Many articles address the issue of the impact of the increasing share of renewable energy from various sources in the economy of the studied countries and their impact on their sustainable development [22–24]. Several studies have examined the dependence of energy consumption for various purposes on many factors influencing it [26–29]. The authors also use regression models that study the relationship between the consumption of energy from renewable sources [30–32] and fossil sources. The research conducted in the article focused on the construction of two econometric models that model variables: final energy consumption in households (energy use) from solid fossil fuels (Y_{t1}) and final energy consumption in households (energy use) from renewable and biofuels (Y_{t2}). A forecast of energy consumption from fossil and renewable sources was also constructed on the basis of estimated models. The models were verified in terms of construction correctness and the possibility of their interpretation and application. The errors of estimated forecasts were also counted.

The paper presents two research hypotheses: the first hypothesis states that household consumption expenditures to a large extent model the final energy consumption for energy purposes (both from fossil and renewable sources). The second hypothesis states that sets of variables describing energy consumption for energy purposes in households differ depending on the sources from which this energy is obtained. Referring to the research, it can be said that the first hypothesis was confirmed empirically, as from the entire set of variables that were considered for research (and there were over 80 different indicators), only five were finally accepted after the initial analysis of correlation coefficients and coefficients of variation. Of these five indicators, it is the final consumption expenditure–households (Euro per capita) that enters the model for both renewable and fossil energy consumption. On the other hand, the truth of the second hypothesis is also confirmed by the fact that the set of variables describing the models (except for final consumption expenditure, households (Euro per capita)) differs significantly depending on the sources from which this energy is obtained.

Based on the forecasts for the estimated models, it can be observed that the consumption of energy from traditional fossil sources in households in EU countries will decrease, which is in line with the EU directives on the consumption of this type of energy. On the other hand, the forecast of energy consumption from renewable sources will increase in the coming years, which is also positive information in relation to the assumptions of the EU energy policy. This will reduce the emission of the main greenhouse gases, especially CO_2, into the environment. Thus, the energy will be more environmentally friendly, there will be no further degradation and devastation of the natural environment of EU countries.

One should be aware that each analysis, especially performed on the basis of econometric models, will be subject to certain risks and uncertainties. This is due to certain limitations in access to time data for the estimated models. Verification of the accuracy of the forecasts obtained is possible only after the publication of current data by Eurostat. In the publication, it was possible to determine the errors of the 'Ex-ante' forecast only for 2021 (due to the unavailability of the data for the later years 2022–2023). Another limitation of the models presented is the fact that such forecasts should also be made for independent variables, increasing the final forecast errors. In addition, the model presented in this respect can be used in practice only for short-term forecasts (for a forecast horizon of up to 3 years).

The currently conducted research is only a contribution to further extended analyses, which will include more detailed analyses such as comparative forecasts of energy consumption from various sources in individual EU member states. In addition, studies based on more detailed (monthly) data are planned, which may show the seasonality of energy consumption. The use of artificial intelligence methods, such as neural networks, is planned to forecast the seasonality of electricity consumption.

Author Contributions: Conceptualization, K.C.-L. and T.P.; methodology, K.C.-L. and T.P.; validation, K.C.-L. and T.P.; investigation, K.C.-L. and T.P.; resources, K.C.-L. and T.P.; data curation, K.C.-L. and T.P.; writing—original draft preparation, K.C.-L. and T.P.; writing—review and editing, K.C.-L. and T.P.; visualization, K.C.-L. and T.P.; supervision, K.C.-L. and T.P. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Publicly available data.

Conflicts of Interest: The authors declare no conflict of interest.

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