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Assessment and Forecasting of Energy Efficiency in Economic Sectors in Poland

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Abstract: The material developed focuses on the analysis of energy efficiency trends in Poland, utilising ODEX indicators for the sectors of industry, transport, households and in general, from 2011 to 2021. The objective of the study is to assess the progress made in energy efficiency and to forecast future trends in these sectors. The methods employed are based on statistical modelling of time series, taking into account sector-specific energy consumption dynamics. The following techniques were employed: linear regression, cluster analysis to identify patterns of change, statistical hypothesis testing for energy efficiency and simplified autoregressive models. The results demonstrated significant improvements in energy efficiency in the industrial sector, stability of the ODEX indicator in the transport sector and gradual improvements in households and overall. The prediction indicates an upward trend in the ODEX indicator in the short term, suggesting an increase in energy demand. However, it also predicts a decline in the long term, which may indicate the effectiveness of future energy efficiency strategies and investments. Consequently, the necessity for continued efforts to increase energy efficiency and further research into the factors influencing energy efficiency in different economic sectors is emphasised.

Keywords: ODEX indicator; energy policy; transport; industry; household

1. Introduction

In the face of the mounting challenges posed by climate change and the imperative to transition to sustainable energy sources, energy efficiency has emerged as a pivotal element of both local and global energy policies [1]. In Poland, a country heavily reliant on coal-fired power generation, enhancing energy efficiency is not merely a response to environmental protection requirements, but also forms part of the strategy to bolster energy security and the competitiveness of the economy [2].

Energy efficiency confers both financial and environmental and energy security benefits [3]. In the context of energy policy implementation, it is crucial to delineate the concept of energy efficiency and to select the most appropriate tools for monitoring progress. The role of indicators is to assess the results achieved, the extent to which targets are being met and to allow for comparative statistics [4].

The current state of research in the field of energy efficiency indicates a number of discrepancies in assessment and forecasting methodologies, as well as differences in the interpretation of the results obtained, making the topic extremely topical and relevant for further research. Studies such as those conducted by Stachura [5], CSO (Central Statistical Office) experts [6] and experts from the European Environment Agency [7] provide valuable data, but there is a clear need for an in-depth analysis of sector-specific conditions in Poland.

The objective of this article is to provide a comprehensive assessment and forecast of energy efficiency in key economic sectors in Poland. The article is based on the ODEX (Aggregate Index Energy Efficiency), which allows progress in improving efficiency to be monitored and the achievements of individual economic sectors to be compared with a baseline value from the year 2000.

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The research hypothesis is that there have been significant changes in energy efficiency in various economic sectors over the past decade, which is reflected in the trends of the ODEX indicators. Furthermore, it is predicted that the current trends in energy efficiency will continue in the future, which can be proven by statistical projections. It should be noted that the term 'economic sectors' is an appropriate designation, as it encompasses the various areas of economic activity, including industry, transport and households. Each of these areas has a significant impact on overall energy efficiency and is an essential element in economic and environmental analyses.

The significance of this work is underscored by the fact that energy efficiency has a direct impact on sustainable development, economic competitiveness and the country's energy policy [8].

In conclusion, this article represents a significant contribution to the existing body of literature on energy efficiency. The comprehensive analysis presented in the article offers valuable insights that will inform future energy policy, particularly in Poland, but also at the international level.

2. Materials and Methods

The data on energy efficiency used as a basis for the analysis was obtained from the Central Statistical Office (CSO), which is the principal public administration body in Poland responsible for collecting and disseminating statistical data. The information was extracted from the CSO's Energy Efficiency Report 2011–2021, which is accessible on the CSO website [9].

This period encompasses significant alterations to energy and economic policy that have influenced energy efficiency in Poland. These include the implementation of novel EU efficiency legislation and substantial investment in energy-efficient technologies.

The examination of a decade's worth of data allows for the observation of long-term trends and significant changes in energy efficiency, which may be less evident over shorter time periods. Ten years of data is sufficient for the application of advanced statistical methods, such as linear regression or autoregressive analysis, which enables the drawing of reliable statistical conclusions.

Finally, this period provides a sufficient number of observations to carry out robust statistical tests, such as the one-sample *t*-test, which is crucial to ensure the statistical significance of the results. Adopting this range of years allowed for a comprehensive examination of the impact of a variety of factors on energy efficiency, from technological to regulatory. As illustrated in Table 1, the ODEX indicator values for the industry, transport, households, and total energy efficiency have exhibited a downward trend from 2011 to 2021.

Table 1. ODEX indicator (unit of measure, values form year 2000 = 100).

Year	Industry	Transport	Households	Total
2011	52.1	92.5	85.4	77.5
2012	51.1	90.1	85.0	76.5
2013	50.4	87.5	84.2	75.3
2014	49.7	84.9	82.2	74.1
2015	48.9	84.7	80.3	73.0
2016	48.3	84.6	78.5	72.4
2017	47.9	84.6	77.8	71.9
2018	47.5	84.6	77.2	71.6
2019	47.0	84.6	76.8	71.2
2020	46.2	84.6	76.6	71.1
2021	45.7	84.6	75.9	70.7

The index of energy efficiency, which serves as a measure of progress in improving energy efficiency at the national level, is expressed in percentage points [10]. The baseline value, taken as 100 points, refers to the year 2000. A decrease in the value of the ODEX index indicates an improvement in energy efficiency, as it indicates less energy consumption for the same or more production. These values permit the observation of trends and the comparison of energy efficiency between different sectors of the economy [11]. ODEX indicators represent a valuable tool in the analysis and management of energy efficiency, as they assist in the identification of areas where further energy savings and reductions in greenhouse gas emissions are possible [12].

Four main sectors were analysed: industry, transport, households and the aggregate for the whole economy. The data provides a comprehensive understanding of the dynamics of energy efficiency change, enabling the identification of sectors that have made the most progress in terms of efficiency, as well as those that require further efficiency measures.

It is important to note the potential limitations of the data. While the ODEX indicator is a widely accepted tool, it may not take into account all factors influencing energy efficiency. These include changes in the structure of the economy, the technological intensity of production and the climatic conditions of a given year. These can have a significant impact on energy consumption. Furthermore, the indicator does not directly reflect the impact of implemented energy and environmental policies, which may be subject to further analysis and discussion.

In this study, we employed hypothesis testing and simplified autoregressive models (AR1) to analyse trends in energy efficiency as measured by the ODEX index. The choice of these statistical methods was guided by several considerations. Hypothesis testing was employed to ascertain whether observed changes in energy efficiency are statistically significant and not due to random fluctuations. The tests were selected based on the nature of the data, which include repeated measurements over several years in multiple sectors. Hypothesis tests, particularly one-sample *t*-tests, were deemed appropriate due to their capacity to cope with small sample sizes and provide robust results even in the presence of distributions that deviate from normality, provided that the central limit theorem holds for larger sample sizes.

The autoregressive model (AR1) was selected for its simplicity and effectiveness in forecasting from time series data. The model assumes that future values have a linear relationship with previous values, which is a reasonable assumption given the gradual changes in energy efficiency over time. The simplicity of the AR1 model allows for a clear interpretation while adequately capturing the temporal dynamics of the data.

The models were constructed on the basis of two key assumptions: that the time series data is stationary and that the residuals are independent. These assumptions were validated through the use of residual plots, which serve to ensure that the models are an appropriate fit to the data without over- or under-fitting.

The Python programming language was employed in conjunction with the Statsmodels library, resulting in the generation of robust, statistically valid conclusions that are supported by well-established data analysis methods. Statsmodels is a Python module that provides a range of classes and functions for the estimation of statistical models, as well as for statistical testing and exploratory data analysis.

This study employed the Statistical Package for the Social Sciences (SPSS) version 26.0, a software package renowned for its comprehensive array of statistical analysis tools. The decision to utilise SPSS was based on its user-friendly interface and extensive functionality.

To enhance the data analysis conducted in SPSS, bespoke Python scripts were developed utilising Python version 3.8. These scripts leveraged the robust Pandas libraries to manipulate the data

3. Results

3.1. Analysis of Trends in Energy Efficiency Developments

The efficacy of energy efficiency strategies in various sectors is corroborated by the OLS regression results, as depicted in Figure 1. The regression outcomes for each sector—industry, transport, households, and overall—furnish empirical proof of year-to-year fluctuations in the ODEX index. The results of the linear regression for the industrial sector demonstrate a high coefficient of determination R^2 of 0.988, indicating a strong fit between the model and the historical data. The p-value for the year variable is less than 0.05, indicating that it is statistically significant in the model. The regression coefficient for the year is -0.6109, indicating that, on average, industrial energy efficiency increases (ODEX decreases) by 0.6109 points for each year.

```
Sektor: Industry

                              OLS Regression Results
=======================================================
Dep. Variable:               Industry   R-squared:
Model:                            OLS   Adj. R-squared:
Method:                 Least Squares   F-statistic:
Date:                Wed, 03 Jan 2024   Prob (F-statisti
Time:                        17:07:48   Log-Likelihood:
No. Observations:                  11   AIC:
Df Residuals:                       9   BIC:
Df Model:                           1
Covariance Type:            nonrobust
=======================================================
                 coef    std err          t      P>|t|
-------------------------------------------------------
const       1280.2109     45.454     28.165      0.000
Year          -0.6109      0.023    -27.095      0.000
=======================================================
Omnibus:                        0.179   Durbin-Watson:
Prob(Omnibus):                  0.914   Jarque-Bera (JB)
Skew:                           0.182   Prob(JB):
Kurtosis:                       2.537   Cond. No.
```

```
Sektor: Transport

                              OLS Regression Results
=======================================================
Dep. Variable:              Transport   R-squared:
Model:                            OLS   Adj. R-squared:
Method:                 Least Squares   F-statistic:
Date:                Wed, 03 Jan 2024   Prob (F-statisti
Time:                        17:07:48   Log-Likelihood:
No. Observations:                  11   AIC:
Df Residuals:                       9   BIC:
Df Model:                           1
Covariance Type:            nonrobust
=======================================================
                 coef    std err          t      P>|t|
-------------------------------------------------------
const       1385.5218    351.631      3.940      0.003
Year          -0.6445      0.174     -3.695      0.005
=======================================================
Omnibus:                        0.302   Durbin-Watson:
Prob(Omnibus):                  0.860   Jarque-Bera (JB)
Skew:                           0.233   Prob(JB):
Kurtosis:                       2.144   Cond. No.
```

```
Sektor: Households

                              OLS Regression Results
=======================================================
Dep. Variable:             Households   R-squared:
Model:                            OLS   Adj. R-squared:
Method:                 Least Squares   F-statistic:
Date:                Wed, 03 Jan 2024   Prob (F-statisti
Time:                        17:07:48   Log-Likelihood:
No. Observations:                  11   AIC:
Df Residuals:                       9   BIC:
Df Model:                           1
Covariance Type:            nonrobust
=======================================================
                 coef    std err          t      P>|t|
-------------------------------------------------------
const       2202.2891    185.294     11.885      0.000
Year          -1.0527      0.092    -11.454      0.000
=======================================================
Omnibus:                        1.483   Durbin-Watson:
Prob(Omnibus):                  0.476   Jarque-Bera (JB)
Skew:                          -0.231   Prob(JB):
Kurtosis:                       1.748   Cond. No.
```

```
Sektor: Total

                              OLS Regression Results
=======================================================
Dep. Variable:                  Total   R-squared:
Model:                            OLS   Adj. R-squared:
Method:                 Least Squares   F-statistic:
Date:                Wed, 03 Jan 2024   Prob (F-statisti
Time:                        17:07:48   Log-Likelihood:
No. Observations:                  11   AIC:
Df Residuals:                       9   BIC:
Df Model:                           1
Covariance Type:            nonrobust
=======================================================
                 coef    std err          t      P>|t|
-------------------------------------------------------
const       1429.4273    134.511     10.627      0.000
Year          -0.6727      0.067    -10.083      0.000
=======================================================
Omnibus:                        2.618   Durbin-Watson:
Prob(Omnibus):                  0.270   Jarque-Bera (JB)
Skew:                           0.089   Prob(JB):
Kurtosis:                       1.564   Cond. No.
```

Figure 1. OLS regression results for the energy efficiency index.

Analyses conducted for transport, households and the general public also demonstrated statistically significant negative regression coefficients, indicating improvements in energy efficiency in these sectors.

Analysing the ODEX indicator data for Poland between 2011 and 2021, it is evident that there have been clear trends in energy efficiency in different sectors of the economy.

The industrial sector demonstrates a consistent decline in the indicator, from 52.1 in 2011 to 45.7 in 2021, indicating a notable improvement in efficiency by over 6 percentage points. This positive change can be attributed to the implementation of modern technologies, the optimisation of production processes and investments in energy-efficient solutions.

In the transport sector, the ODEX index also demonstrates a decline, from 92.5 in 2011 to 84.6 in 2021. This suggests that energy efficiency in transport is improving, potentially due to the modernisation of vehicle fleets and the promotion of clean transport modes.

The household sector also exhibits an enhancement in efficiency, from 85.4 in 2011 to 75.9 in 2021. The reduction in the value of the indicator in this sector can be attributed to improvements in thermal insulation of buildings, the implementation of more efficient heating systems and an increase in consumer energy awareness.

Overall, the ODEX indicator for total energy consumption in Poland has decreased from 77.5 in 2011 to 70.7 in 2021, indicating an overall improvement in the country's energy efficiency. Nevertheless, it is essential to acknowledge that each year brings a distinctive set of challenges and circumstances that may have influenced these outcomes, including alterations in the economy, energy policy, energy commodity prices or the implementation of new regulations.

It should be noted, however, that these analyses are limited by the small number of observations (n = 11 years of data), which may affect the stability of the estimation and interpretation of statistical tests such as the Omnibus or Jarque–Bera test. These tests are more reliable with a larger number of observations. Furthermore, high conditional number values may indicate the potential for multicollinearity in the data. However, this is unlikely in the context of a simple linear model with one independent variable.

3.2. Cluster Analysis

The application of cluster analysis to the grouping of years according to similarity in patterns of energy efficiency change can assist in the identification of periods exhibiting similar characteristics. Typically, cluster analysis commences with the utilisation of the elbow method to determine the optimal number of clusters. This method involves the plotting of inertia values (the sum of the squares of the distances of points from their nearest cluster centres) for different numbers of clusters, with the subsequent identification of the 'elbow'—the point at which the increase in inertia decreases rapidly—as illustrated in Figure 2.

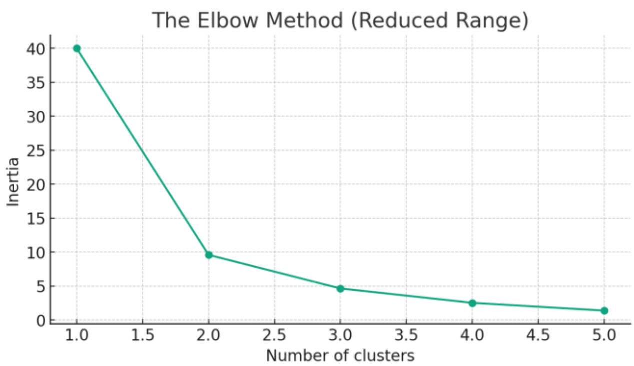

Figure 2. The identification of the optimal number of clusters using the elbow method.

The cluster analysis presented in Figure 3 employs a colour-coding scheme to differentiate between clusters. Each colour represents a group of years during which ODEX indicators exhibited comparable characteristics or patterns of change. This grouping facilitates the visual identification of periods characterised by uniform trends in energy efficiency. In the elbow drawing method for a reduced range of the number of clusters, it can be observed that the inertia decreases significantly between 1 and 2 clusters, and then the decrease is more gradual. While there is no clear 'elbow' to indicate the optimal number of clusters, the choice of 3 clusters may be reasonable, as after this number the reduction in inertia is smaller and no longer benefits as much. Consequently, by adopting three clusters, it is possible to perform a comprehensive cluster analysis and observe how the years cluster in relation to each other in terms of ODEX indicators.

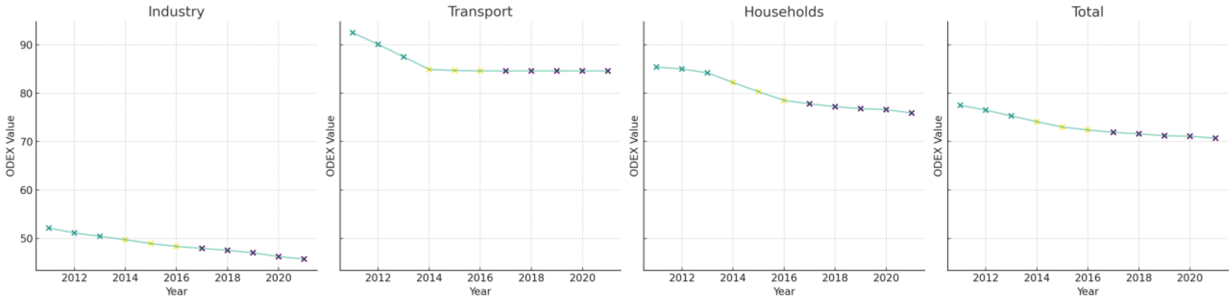

Figure 3. Cluster analysis of energy efficiency in Poland.

A cluster analysis with three clusters reveals that the years were divided into three groups:

- Cluster 0: 2017–2021, which are the latest in the dataset and may reflect the latest trends in energy efficiency.
- Cluster 1: 2011–2013, which are the earliest years in the analysis and may represent the starting point for changes in energy efficiency.
- Cluster 2: 2014–2016, which lie between the other two groups, may reflect a period of transition.

In the scoring charts for each sector, the colours indicate cluster affiliation. As anticipated, the years from each cluster are closely grouped, suggesting similar ODEX indicator values within the cluster. This demarcation may reflect periods when specific energy policies or technological innovations have influenced energy efficiency.

3.3. The Hypothesis Testing

Statistical hypothesis testing represents a pivotal step in scientific research, serving to verify whether observed results are statistically significant or may be the result of random variation. The fundamental concepts at play are the null hypothesis (H0) and the alternative hypothesis (H1). The null hypothesis represents an initial assumption about the data, typically indicating the absence of an effect or difference. The alternative hypothesis is the hypothesis that is accepted when the null hypothesis is rejected. The following hypotheses have been formulated:

Null hypothesis (H0): It can be concluded that there is no statistically significant change in energy efficiency over the period analysed.

Conversely, there is a statistically significant change in energy efficiency over the period analysed.

This is the standard approach used when investigating whether the observed data differs from a particular value. The following equation was employed:

$$\mathrm{t} = \frac{\overline{x} - \mu_0}{s/\sqrt{n}} \tag{1}$$

t is the value of the *t*-test statistic;
$\overline{x}$ is the average observed in the sample;
μ_0 is the reference value against which we compare the average;
s is the standard deviation of the sample;
n is the number of observations in the sample.

The statistical significance of the changes in energy efficiency within each sector was confirmed through *t*-test analysis. The results, presented in Table 2, demonstrate that all sectors—industry, transport, households, and the aggregate total—have exhibited statistically significant improvements in energy efficiency over the period studied.

Table 2. T-test results for one sample of ODEX indicators.

Sector	t-Statistics	*p*-Value
Industry	−83.60	<0.001
Transport	−16.72	<0.001
Households	−18.39	<0.001
Total	−38.17	<0.001

One-sample *t*-tests for the ODEX indicators revealed that the mean values of the indicators from 2011 to 2021 are statistically distinct from the 2000 baseline. The *p*-value is considerably less than the standard significance level of 0.05, thereby allowing the null hypothesis (H0) to be rejected. These findings thus indicate a notable enhancement in energy efficiency across the analysed sectors in comparison to the base year.

Analyses and comparisons of the energy efficiency of individual economic sectors with the aggregate for the country as a whole are a key element in understanding the dynamics of energy consumption and identifying potential areas for improvement. Such analysis provides valuable insights for policy makers, economic decision makers and researchers, enabling a better understanding of how individual sectors contribute to the overall energy balance of the country. The results of the statistical tests and associated *p*-values for comparing the 'Industry', 'Transport' and 'Households' sectors with the 'Total' aggregate are presented below.

Given the limitations associated with the normality of the distribution for the 'Transport' sector, the use of the traditional *t*-test for independent samples may not be appropriate. Consequently, an alternative statistical method was employed, namely the Mann–Whitney U test (also known as the Wilcoxon test for two independent samples). This is a non-parametric test used to compare two independent groups. Unlike parametric tests, it does not require an assumption of normality of distribution and can be used to assess whether two independent samples come from the same distributions. The selection of an appropriate method is contingent upon the nature of the data, the objective of the analysis and the specific assumptions inherent to the study in question. In the context of the available data, given that the assumption is to compare a sector with the aggregate 'Total' in order to ascertain the degree to which household energy efficiency differs from the total energy efficiency of all sectors, the Mann–Whitney U test may be a suitable method to assess the significance of these differences without assuming normality of distribution. The following equation was employed:

$$U_1 = R_1 - \frac{n_1(n_1+1)}{2} \quad U_2 = R_2 - \frac{n_2(n_2+1)}{2} \tag{2}$$

R_1 and R_2 is the sum of the ranks for the first and second group
n_1 and n_2 is the size of the first and second groups

In order to assess the differences in energy efficiency between individual sectors and the economy as a whole, the Mann-Whitney U-test was applied, as demonstrated in Table 3.

Table 3. The results of the Mann–Whitney U test for the purpose of comparing the sectors with the overall aggregate.

Sector	Test Statistics	*p*-Value
Industry	0.0	0.000082
Transport	121.0	0.000080
Households	116.0	0.000304

A comparison of the results presented in the table above reveals statistically significant differences between the various sectors and the aggregate 'Total'. This indicates a notable divergence in energy efficiency between the sectors under analysis and the wider economy. The test statistic provides further insight into the relationship between the ranks of the compared groups and the low *p*-values confirm the significance of these differences. Nevertheless, the values of the test statistic exhibit discrepancies, which provide insights into the nature of these differences and their potential significance. These insights will be presented in the subsequent section of the article, the discussion.

In the context of the analyses comparing the energy efficiency of different economic sectors (namely, 'Industry', 'Transport' and 'Households') with the aggregate 'Total' using the Mann–Whitney U test, a key objective was to test two hypotheses for each sector.

The null hypothesis (H0) states that there is no statistically significant difference in energy efficiency between the sector and the aggregate 'Total'.

The alternative hypothesis (H1) states that there is a statistically significant difference in energy efficiency between the sector and the aggregate 'Total'. The results of the statistical tests indicate that there is a statistically significant difference in energy efficiency between the sector and the aggregate 'Total'. All tests carried out result in the rejection of the null hypotheses (low *p*-value), which implies that for each of the sectors analysed, there are statistically significant differences in energy efficiency compared to the average energy efficiency at an economy-wide level. This indicates that the 'Industry', 'Transport' and 'Households' sectors exhibit characteristics that diverge from the prevailing trend, necessitating the implementation of targeted measures to enhance energy efficiency in these domains.

3.4. Future Energy Efficiency Trends

The historical analysis of the ODEX indicator has revealed patterns and trends that are essential to evaluating past efforts to improve energy efficiency. However, as we stand on the threshold of significant environmental and technological change, it becomes increasingly important to look ahead, projecting these trends for years to come. This forward-looking analysis not only anticipates the challenges and opportunities that lie ahead, but also serves as a guide for strategic planning and policy formulation to achieve a more energy-efficient and sustainable future.

In modelling and forecasting the Operational Energy Efficiency Index (ODEX) for different economic sectors, it is important to use a methodology that strikes a balance between model accuracy and understandability. The decision to choose a simplified first-order autoregressive model (AR1) is based on several key considerations that translate into the reliability and practical value of the analyses performed. These include:

- The effectiveness of this approach in capturing temporal relationships is particularly useful for the ODEX indicator, where past values can be strong predictors of future trends.
- The simplicity and interpretability of this model are also noteworthy. In comparison to more complex models such as ARIMA, this model is characterised by greater interpretability. This is evidenced by the fact that while the AR component was significant, the MA component no longer made a significant contribution to the model.
- Practical verifiability: This allows for easier verification and comparison of results with available historical data and future observations. This is important for ongoing monitoring of the effectiveness of energy policies and identifying areas for intervention.

The following equation was employed:

$$\mathrm{Y_t} = \mathsf{C} + \varnothing \mathrm{Y_{t-1}} + \in_{\mathrm{t}} \quad (3)$$

$\mathrm{Y_t}$ represents the value of the variable at time t;
C is a constant;
$\varnothing$ is the autoregression coefficient, which indicates the extent to which the previous value

Y_{t-1} represents the value of the variable at time $t-1$;
$\in_t$ is the random error (noise) at time t, assuming that $\in_t \sim N(0, \sigma^2)$, i.e., it has a normal distribution with mean equal to 0 and variance σ^2.

The parameter values C and $\varnothing$ are estimated on the basis of historical data.

The data presented in Table 4 indicates a discernible, albeit slight, increase in the ODEX indicator across all sectors between the years 2025–2027. This may suggest a gradual reduction in energy efficiency and an increase in energy use in relation to sectoral activity. The overall upward trend in the ODEX indicator points to potential challenges in improving energy efficiency at an economy-wide level.

Table 4. The ODEX index predictions generated by AR1 models.

Year	Industry	Transport	Households	Total
2025	45.77	84.86	76.02	70.78
2026	45.85	85.09	76.17	70.88
2027	45.93	85.29	76.32	70.97

An assessment of the fit of the AR1 models for all sectors was also carried out, with a focus on the diagnostic statistics of the model residuals using the Ljung–Box test. This analysis verified that the residuals from the model are close to a normal distribution and do not show autocorrelation, which could indicate an inappropriate model fit. In addition, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) values were evaluated to assess the overall quality of the model.

One of the fundamental aspects of regression analysis is the examination of residuals, which serves to ensure the model's adequacy. The residual analysis for the industrial sector, which encompasses an investigation of the distribution of residuals and their autocorrelation, is depicted in Figure 4.

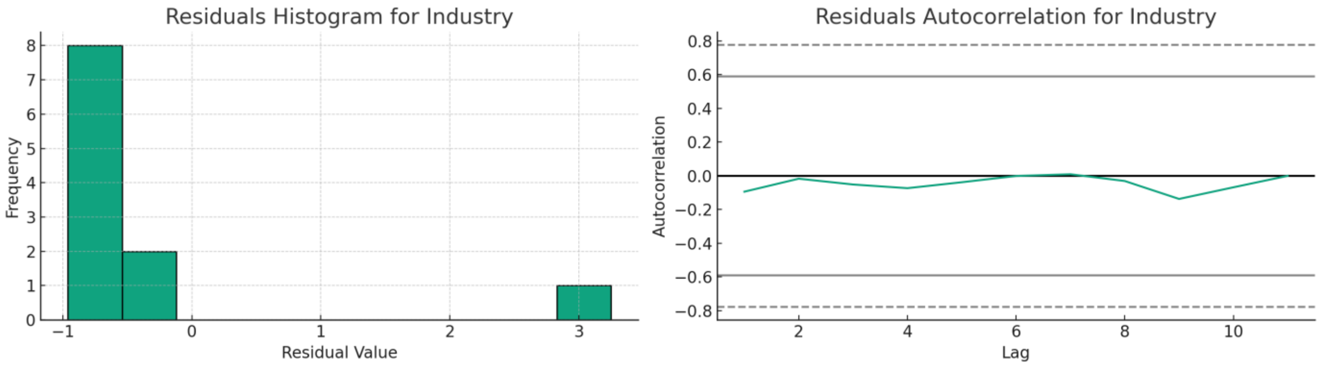

Figure 4. The results of the residual analysis for the industrial sector.

The histogram of the residuals analysis for the industrial sector displays a distribution that is close to normal. Additionally, the autocorrelation plot indicates that there is no significant autocorrelation, which suggests that the AR1 model is adequately fitted to the data in this sector.

In our assessment of model diagnostics for the household sector, we examined the distribution of residuals and their autocorrelations to ascertain whether there were any deviations from the assumed model conditions. The findings of this analysis are illustrated in Figure 5.

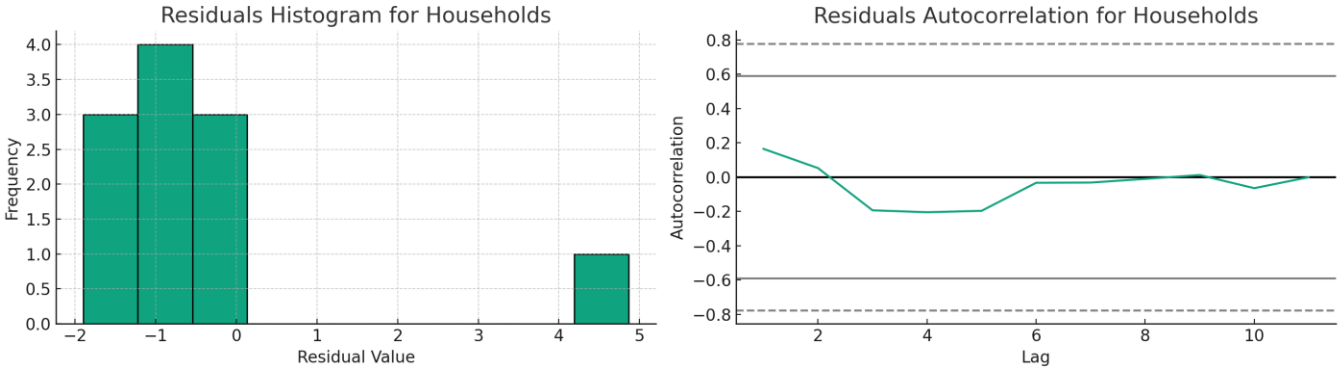

Figure 5. The results of the residual analysis for the household sector.

The residual analysis for the household sector also indicates a distribution that is close to normal. Furthermore, the autocorrelation plot shows no evidence of autocorrelation problems, which suggests that the AR1 model is effective in this context.

A residual analysis was also conducted on the regression model for the transport sector. Figure 6 presents the residuals histogram and autocorrelation plot for this sector.

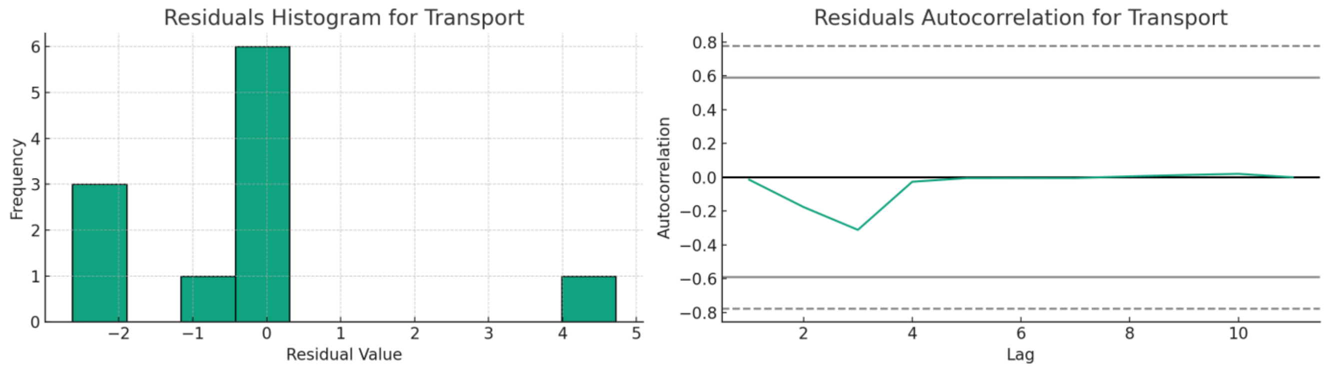

Figure 6. The results of the residual analysis for the transport sector.

Similarly, the histogram of the residuals exhibits a near-normal distribution and the absence of significant peaks in the autocorrelation plot indicates that the AR1 model is performing well with the data. The comprehensive assessment of our regression model also includes an evaluation of the residuals for the aggregated data across all sectors. Figure 7 illustrates the residuals histogram and autocorrelation plot for the total dataset, which allows us to verify the normality of residuals and the assumption of no autocorrelation.

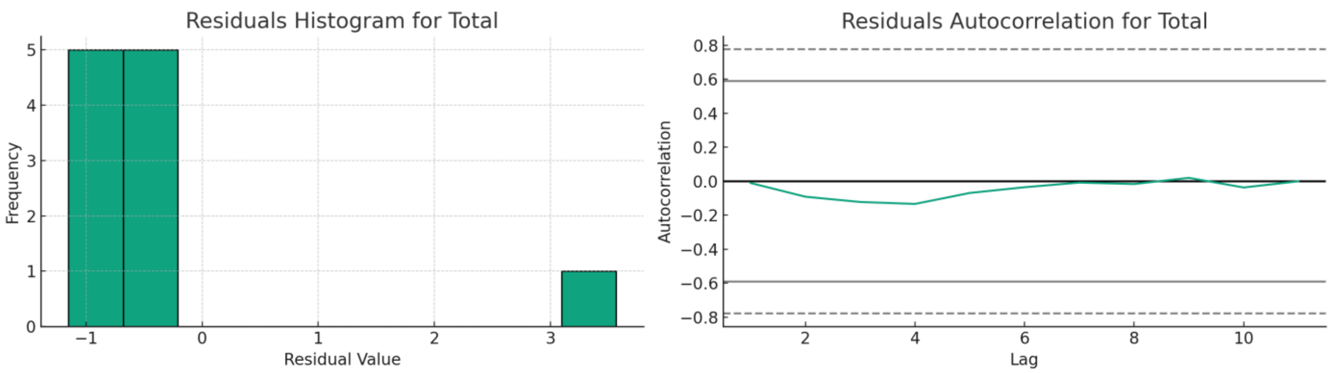

Figure 7. The analysis of total residuals.

The results are comparable to those observed in other sectors, with a histogram indicating the normality of the residual distribution and an autocorrelation plot demonstrating the absence of significant autocorrelation in the residuals.

The residual histograms for all sectors appear to be close to a normal distribution, which is a positive indicator. The autocorrelation plots do not indicate the presence of significant autocorrelation in the residuals, suggesting that the models effectively incorporate the information contained in the data.

The Ljung–Box test is a statistical test used to assess the presence of significant autocorrelations in the time series or model residuals at a given lag level. This test is particularly useful in the context of time series modelling, where it is important that the model residuals (errors) are white noise, i.e., show no autocorrelation. This test helps to verify whether the model adequately explains the data, or whether there are additional patterns that the model does not capture. The test statistic Q in the Ljung–Box test is calculated as:

$$Q = n\,(n+2)\,€_{k=1}^{h}\,\frac{\hat{p}_k^2}{n-k} \quad (4)$$

n is the number of observations;
h is the number of delays taken into account in the test;
$\hat{p}_k$ is the estimated autocorrelation of the residuals at lag k.

The following hypotheses were adopted:

- Null hypothesis (H0): There is no autocorrelation in the series of residuals up to the h-th lag.
- Alternative hypothesis (H1): There is autocorrelation in the series of residuals to the h-th lag.

The p-values for each sector are significantly higher than the typical significance threshold (0.05), indicating that there is no evidence to reject the null hypothesis of no autocorrelation of the residuals. This provides further evidence that the models are a good fit to the data.

AIC and BIC are two statistics used to assess the quality of a statistical model and to compare different models, taking into account their fit to the data and the complexity of the model. Both AIC and BIC are frequently employed in time series analysis to identify the most suitable model. These values are calculated according to the following equation:

$$\text{AIC} = 2\text{k} - 2\ln(\text{L}) \quad (5)$$

$$\text{BIC} = \ln(\text{n})\text{k} - 2\ln(\text{L}) \quad (6)$$

n is the number of observations;
k is the number of parameters in the model;
L is the maximum value of the plausibility function for the model.

In order to assess the suitability of the autoregressive models applied to the ODEX index data, both AIC and BIC were calculated in order to evaluate the quality of the models, as illustrated in Table 5.

Table 5. The AIC and BIC results for AR1 models fitted to ODEX index data.

Sector	AIC	BIC
Industry	31.448	32.642
Transport	46.279	47.472
Households	42.905	44.099
Total	34.629	35.823

The AIC and BIC for industry are relatively low, indicating a good fit of the model given its complexity. However, the AIC and BIC for transport are higher than for industry, which may indicate that the model has greater complexity relative to the number of observations available, which may affect the overall quality of the fit. Furthermore, the AIC and BIC for households are higher, suggesting a potentially weaker model fit. In contrast, the AIC and BIC for overall are close to those for industry, indicating a relatively good model fit.

Over the last 15 years, EU legislation on energy efficiency has undergone significant changes. In 2023, the legislators increased the energy efficiency target, i.e., the target to reduce the EU's final energy consumption, to 11.7% by 2030. A projection of the ODEX indicator for 2030 was therefore made. The results of the analyses carried out are presented in Table 6.

Table 6. The ODEX indicator projections generated by AR1 models for the year 2030.

Sector	Forecast ODEX
Industry	42.99
Transport	84.60
Households	73.12
Total	67.90

The observed upward trend of the ODEX indicator in the short term, followed by a subsequent decline in the long term, may be indicative of a combination of time factors, technological progress and effective energy policies. Such results emphasise the importance of long-term planning and investment in energy efficiency, which are key to achieving sustainability and reducing environmental impacts.

In order to ensure the relevance and applicability of our projections for future energy efficiency trends in Poland, it is essential to consider them within a broader context. The projections made to 2030 are not only based on past and current data, but also take into account several key factors that could influence future outcomes. These include anticipated economic growth, expected advancements in energy-efficient technologies and potential changes in national and European energy policies.

For example, Poland's economic growth, which directly impacts industrial activity and energy consumption, is projected by various economic forecasts to continue at a moderate pace. This growth will likely influence energy demand and efficiency trends in the industrial and household sectors. Furthermore, ongoing advancements in technology, such as the development and decreasing costs of renewable energy sources and energy-efficient appliances, are expected to play a critical role in shaping future energy consumption patterns.

Furthermore, policy decisions at both the national and European Union levels, such as commitments to reduce carbon emissions and improve energy efficiency, will significantly impact energy strategies within Poland. The European Green Deal and Poland's Energy Policy 2040 are examples of such frameworks that aim to foster a significant shift towards more sustainable energy use over the next decade.

Including these contexts allows for a more comprehensive understanding of the projections, giving them weight and making them far from worthless. By acknowledging these factors, we provide a foundation for our projections that is both empirically grounded and informed by a comprehensive analysis of anticipated future developments.

4. Discussion

ODEX represents a pivotal instrument in the assessment of energy efficiency, enabling meticulous analysis of the advancement in energy savings and the identification of areas in need of further action to achieve sustainability goals [13]. A comparison of the effectiveness of ODEX with an alternative energy efficiency indicator, such as the energy intensity index with structural effects removed, calculated using the logarithmic mean Divisia Index (LMDI) decomposition technique, shows that both methods are highly valuable [14–17].

The introduction of new energy performance indicators, such as energy efficiency indicators, allows for the optimisation of energy consumption in different economic sectors [18]. A review of research on the assessment and prediction of energy efficiency in economic sectors reveals a considerable diversity of approaches and methods. Research in this field has focused on the comparison of energy efficiency indicators, the identification of criteria for the energy sector, the application of predictive analytics to enhance energy efficiency in industrial and transport companies and methods to improve energy efficiency in the residential sector [19–23].

The analysis of ODEX indicators and the implementation of energy efficiency measures are consistently incorporated into the energy strategies of many countries. Case studies of countries such as Slovenia, Switzerland and others point to the need for further action to achieve national energy efficiency targets [24–28].

While the ODEX Energy Efficiency Index provides a robust framework for assessing energy efficiency trends across sectors, it is important to recognise its limitations. One of the main limitations of the ODEX indicator is that it may be overly simplistic in its ability to accurately measure the nuances of energy efficiency improvements. While the ODEX indicator is effective in capturing overall trends, it may not fully reflect the complex interplay between sectoral policies, technological advances and economic change. For instance, it fails to differentiate between energy savings resulting from technological innovation and those resulting from economic downturns or reduced industrial activity [29].

Furthermore, the ODEX indicator is based on a fixed base year, which may inaccurately reflect current changes in energy intensity due to structural changes in the economy or shifts towards more service-oriented sectors. These factors can lead to misleading interpretations of energy efficiency progress if not accurately accounted for [30]. Consequently, while ODEX offers valuable insights, it is advisable to complement it with other qualitative measures and analyses in order to gain a more comprehensive understanding of the energy efficiency landscape, which may be the subject of a subsequent publication.

In order to analyse the improvements in energy efficiency within Poland's economic sectors, it is essential to consider the broader economic context that influences these sectors. For example, the gross domestic product (GDP) of Poland has demonstrated a consistent increase over the past decade, which may be correlated with changes in energy consumption and efficiency. An understanding of the economic growth dynamics provides insights into how energy demands have evolved in response to increased industrial activities and economic output. Additionally, the distribution of the workforce across different sectors can significantly affect energy efficiency trends. The number of workers in each sector exerts a significant influence on the overall energy consumption patterns. For instance, sectors with larger workforces, such as industry and transport, may exhibit disparate energy efficiencies due to varying operational scales and the implementation of energy-saving technologies.

To contextualise our findings, examining Poland's GDP alongside the number of workers in key sectors, such as industry, transport and household, can provide a more comprehensive understanding of the factors influencing energy efficiency. For instance, as the industrial sector employs a considerable proportion of the workforce and contributes significantly to the GDP, improvements in its energy efficiency can have a particularly impactful effect on the national scale.

This approach not only enriches our discussion but also aligns with the global perspective on the intertwined relationship between economic factors and energy use, as well as sustainability efforts. The research conducted for this thesis provided an analysis of energy efficiency trends in different economic sectors, using ODEX indicators as the main measurement tool. The results showed significant improvements in energy efficiency in the industrial sector, which is in line with previous studies indicating the success of energy policies and technological innovations in this area.

However, the stability of ODEX indicators in the transport sector suggests that progress is less evident in this area, highlighting the need for further action to increase energy efficiency. In order to achieve this, there is a need to promote green mobility, cycling and investment in alternative energy sources, which is in line with current European trends. The results for the household sector shed light on the potential for improvement through thermo-modernisation of buildings, more efficient heating systems and raising public awareness.

Cluster analysis and hypothesis testing provided additional evidence of clear trends in the data, confirming the research hypothesis of significant changes in energy efficiency over the past decade. These results indicate the effectiveness of existing strategies and areas where further research and interventions are needed.

The projections made for the ODEX indicator show an increase in value in 2025, 2026 and 2027, followed by a decrease in 2030. This necessitates the consideration of a number of potential factors and the context in which these changes may occur. An increase in the value of the ODEX indicator in the short term may be attributed to temporary factors, such as increased energy demand as a consequence of rapid economic growth or periodic increases in energy prices that delay investments in energy efficiency. Conversely, a decrease in the projected ODEX in 2030 may reflect the effects of implementing long-term strategies and policies to improve energy efficiency. This may include investment in new technologies, increased use of renewable energy sources, implementation of stricter energy consumption standards, as well as extensive education programmes and financial incentives for businesses and households. The projected decline in 2030 may also reflect expectations of mass adoption of new efficiency technologies that are currently in development or early implementation.

The observed improvements in energy efficiency across various sectors in Poland can be attributed in part to specific national and EU policy measures. For instance, the implementation of the EU's Energy Efficiency Directive and Poland's National Fund for Environmental Protection and Water Management incentives have played a pivotal role in promoting energy-efficient technologies and practices. These policies have not only encouraged the adoption of more efficient technologies but have also set regulatory frameworks that industries must follow. This is likely to have contributed to the positive trends observed in the industrial and household sectors. Furthermore, our findings highlight several areas for future research that could provide deeper insights into energy efficiency trends. One key area is the investigation of sector-specific responses to policy changes. Future studies could focus on comparative analyses of different sectors' adaptability and the effectiveness of specific policy interventions over time. Furthermore, research could investigate the impact of emerging technologies, such as smart grids and IoT-based energy management systems, on energy efficiency. Understanding these impacts could inform policymakers about where to direct future funding and support.

Moreover, given the limitations identified in the use of the ODEX indicator, further research could develop or refine methodologies for more accurately capturing the nuances of energy efficiency improvements across diverse economic sectors. Such an approach would not only enhance the accuracy of energy efficiency assessments but also provide a more comprehensive understanding of the impacts of policy measures.

Changes in energy policy, both nationally and internationally, may contribute to a long-term decline in ODEX. International agreements on climate change, national emission reduction plans and initiatives to promote green energy can have a significant impact on future energy consumption trends. Furthermore, long-term changes in the economic structure, such as the shift from heavy industry to services and information technology, as well as demographic changes, may naturally lead to a reduction in the energy intensity of the economy. Future research could usefully focus on a more thorough understanding of the reasons for differences in energy efficiency between sectors and on assessing the impact of new technologies and regulatory changes. Furthermore, an investigation into the influence of societal changes and consumer behaviour on energy efficiency may also prove to be a fruitful avenue of enquiry.

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