Theoretical Economics Letters, 2025, 15(4), 904-917
https://www.scirp.org/journal/tel
ISSN Online: 2162-2086
ISSN Print: 2162-2078

An ARDLX-Based Multi-Method Analysis of Energy CPI with Composite Transportation Indices

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How to cite this paper: Kastas, E., Voudouris, V., & Kyriazi, F. (2025). An ARDLX-Based Multi-Method Analysis of Energy CPI with Composite Transportation Indices. *Theoretical Economics Letters, 15,* 904-917.
https://doi.org/10.4236/tel.2025.154050

Received: February 4, 2025
Accepted: August 3, 2025
Published: August 6, 2025

Abstract

In this paper, we construct and evaluate macroeconomic and transportation-based indices to assess their predictive power in forecasting the Energy Consumer Price Index (CPI). We introduce three novel indices that incorporate global crude oil prices, industrial production, deep-sea freight, air transportation, and motor vehicle equipment. To assess their forecasting ability, we compare their performance against AR(1) and AR(2) benchmark models using rolling window approaches and two estimation methods: ordinary least squares and quantile regression. The results demonstrate that our proposed indices consistently outperform the benchmarks across most model specifications and window lengths, with transportation-related indicators showing particularly strong and robust predictive performance for future energy price trends.

Keywords

Forecasting, Energy Consumption, Leading Indicators, ARDLX Models, Transportation Indices

1. Introduction

Gasoline, fuel oil, electricity, and natural gas are key components of household and industrial energy consumption. They represent distinct forms of energy used for transportation, heating, and power supply. Figure 1 presents the evolution of these energy resources in the United States from 1957 to 2025. It is evident that the consumption of each energy resource has increased significantly during this time period. One possible explanation, according to Wei et al. (2019), is the economic and population growth.

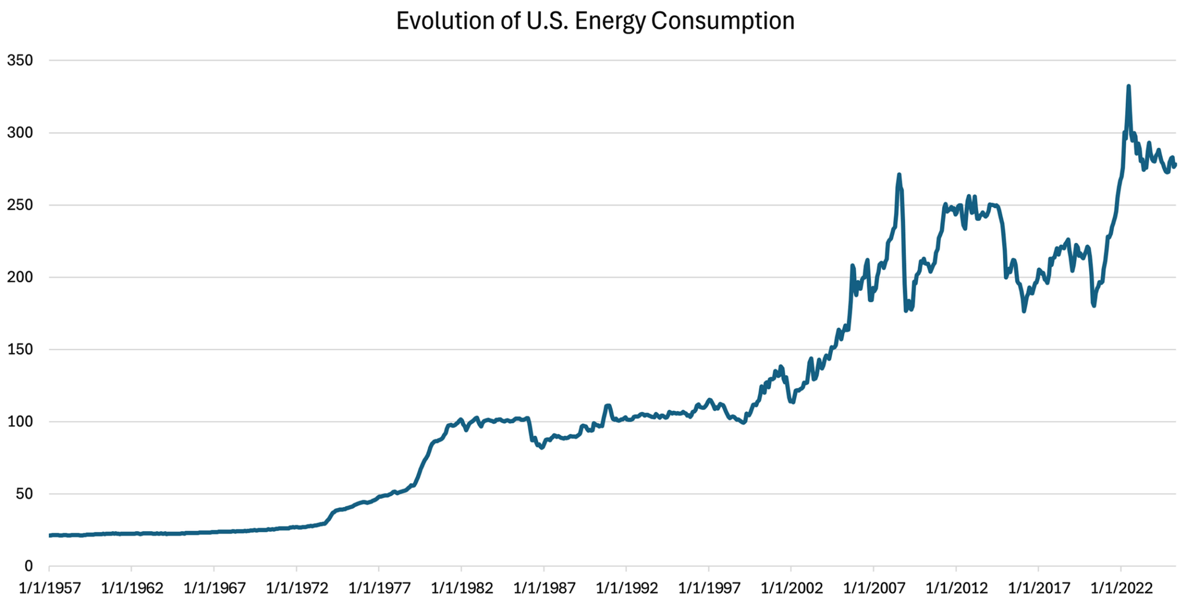

Figure 1. The evolution of U.S. energy consumption index.

The significant increase in energy consumption across various resources clearly reflects the rapid growth in both the economy and population. This rise not only points to higher demand but also contributes to increased environmental pollution. Managing energy use effectively is crucial to addressing these challenges, and a key part of that is being able to accurately predict future energy consumption. Forecasting helps us understand patterns, identify how energy use relates to environmental impacts and business activities, and optimize current systems and resources to meet specific goals. Because of this, forecasting energy consumption is fundamental to successful energy management strategies aimed at improving efficiency and sustainability (Smith et al., 2007; Suganthi & Samuel, 2012; El Maghraoui et al., 2022).

In this paper, we make a three-fold contribution. First, we examine how well a set of transportation variables can forecast future energy consumption using leading indices[1]. We construct three distinct leading indices that combine Brent Crude, industrial production, deep-sea freight transportation, air transportation, and motor vehicle equipment data. We then evaluate these indices as straightforward and effective tools for summarizing information about future energy consumption growth trends. Second, to test the robustness of our forecasts and enhance their forecasting performance, we use the conventional AR(1) and AR(2) models as our baseline benchmarks. Third, we implement different rolling window approaches to enhance robustness by emphasizing the most recent data. Our results are promising in incorporating these proposed indices into ARDLX models that improve forecasting performance, especially in terms of Mean Square Error (MSE) and Quantile Regression (QR) approach, where we observe the greatest improvements com-

[1]For the successful use of leading indicators models in forecasting, see also Prokopos and Kyriazi (2025), Baimpos and Kyriazi (2025), and Guerard et al. (2020, 2023).

pared to the benchmark models.

The rest of the paper is structured as follows: In Section 2, we present a brief relevant literature; in Section 3, we delve into our methodology and forecast evaluation; Section 4 analyzes our results and finally, in Section 5, we conclude with some policy implications.

2. Literature Review

Early energy forecasting attempts, particularly before the 1970s, mostly relied on using historical data trends to predict future energy needs. However, the oil price shocks of the 1970s exposed the shortcomings of these approaches and revealed the necessity of including multi-factor data. Stratton (1979) reasoned that productive energy forecasting must be cross-disciplinary, including indicators from sectors such as economics, engineering, political science, and environmental studies. Consequently, Hamilton (1983) established the foundational understanding of how energy prices affect economic performance, which is essential for accurate energy forecasting. Hamilton presented how the oil price increases have been instrumental in triggering economic downturns. More recent research has explored the importance of energy price uncertainty. Punzi (2019) investigates the impact of energy price volatility on macroeconomic patterns in greater detail. Punzi concludes that increases in energy price uncertainty reduce GDP, consumption, investment, and labor supply in the United States.

Despite the significance of energy prices in influencing macroeconomic conditions, accurately forecasting energy values remains a complex task. Alquist and Kilian (2010) present the weaknesses of crude oil futures prices in predicting future spot prices. Their analysis showed that oil futures' prices regularly underperformed no-change forecasts when predicting future spot prices. In response to single-predictor models, Baumeister and Kilian (2015) made advances in forecasting approaches, achieving significant results in forecasting oil prices by combining six different econometric models. Ferrari et al. (2019) propose a sparse dynamic factor model to predict global energy commodity prices, arguing that careful selection of macroeconomic variables improves forecasting accuracy relative to traditional time series models and naive machine learning techniques. Billé et al. (2023) show that simple models focusing on macroeconomic fundamentals and exogenous fundamental variables present better forecasting accuracy than both traditional autoregressive models and more complex machine learning techniques. This is particularly true when predicting hourly day-ahead electricity prices. Recent research highlights the evolving role of machine learning approaches in energy price forecasting. Xu et al. (2025) develop a hybrid forecasting framework that combines both macroeconomic and financial market indicators with machine learning models such as LSTM, GRU, and MLP, producing promising results on crude oil prices.

As referenced above, forecasting models utilizing multiple indicators such as industrial production, Brent crude oil prices, maritime, air, and vehicle transportation can achieve propitious forecasting results. With that said, industrial production is recognized as a vital macroeconomic indicator, linked to energy demand. Kilian (2009) presents that global industrial production drives oil price fluctuations. Volatility in industrial production can provide insight into energy consumption. Consistent with this view, Baumeister et al. (2020) underline the superiority of global industrial production for predicting real oil prices and petroleum consumption. Brent crude oil spot price remains at the center of determining consumer energy costs, as it affects the prices of gasoline, heating oil, and other energy goods. Furthermore, transportation activities are among the most energy-intensive sectors of the economy, affecting overall energy demand. Notteboom and Rodrigue (2008) display the challenges of forecasting shipping container flows given the volatility of macroeconomic indicators. They argue that container flows lead to industrial demand and energy consumption, indicating energy price trends. Small and Van Dender (2007) show that fuel efficiency improvements have a weaker effect on travel demand than previously thought. Graham and Glaister (2004) provide in-depth estimates of the elasticity of road traffic demand concerning fuel prices and income levels, further reinforcing the correlation between transportation, macroeconomic trends, and energy consumption. Baumeister et al. (2020) argue in favor of including transportation-related indicators to improve forecasting ability.

Despite the width of existing research, gaps remain. Few studies have combined solid macroeconomic and transportation-related variables to forecast energy prices. In addition, limited work has evaluated model performance against multiple benchmarks in the context of consumer energy prices. In this study, we try to address these gaps by utilizing a diverse set of predictors and assessing the accuracy relative to two benchmark models.

3. Data and Methodology

Data and Forecast Evaluation

Our variables were collected from the official Federal Reserve Economic Data (FRED) system. They are monthly time series covering the period from January 1993 to March 2025. The independent variables in our analysis include the global price of Brent Crude, industrial production, deep-sea freight transportation, air transportation, and motor vehicle equipment. The dependent variable is the Energy Consumer Price Index. The magnitude of the selected variables stems from their fundamental role in forecasting energy prices, specifically the Energy Consumer Price Index. More specifically, the oil price shocks have a direct and asymmetric effect on retail energy consumer prices (Huang, Hwang, & Peng, 2005; Baumeister & Peersman, 2013; Gao, Kim, & Saba, 2014; Valadkhani, 2014). Empirical studies underline the impactful link between industrial production and energy demand, both in the short and the long term (Kümmel, 1982; Kilian, 2009; Zachariadis, 2007; Baumeister et al., 2020). Fluctuations in maritime freight transportation are associated with energy demand volatility, where disruptions in shipping efficiency and port congestion influence energy inflation trends (Notteboom & Rodrigue, 2008; Karamperidis, Melas, & Michail, 2024; Tiwari et al., 2024). Similarly, air transportation activity guides jet fuel consumption and contributes to energy price spikes, ultimately passed on to consumers (Wadud, 2015; Lin & Zhu, 2020; Emami Javanmard, Tang, & Martínez-Hernández, 2024). Lastly, energy price spikes—particularly gasoline—shift vehicle purchasing behavior to more fuel-efficient solutions, altering overall energy usage and hence retail energy prices (Graham & Glaister, 2004; Li, Timmins, & von Haefen, 2009; Kaufmann, 2023).

To evaluate the accuracy and forecasting capability of our models, we employ two widely used measures, the Mean Squared Error (MSE) and the Mean Absolute Error (MAE). When we split our sample into two components, namely the rolling window n_0 and the evaluation window n_1, we define the MSE and MAE for each model as follows:

$$\mathrm{MSE}\left(m,n_1\right) \overset{\text{def}}{=} n_1^{-1}\sum\nolimits_{t=n_0+1}^{n}\hat{\epsilon}_t^{m,2}$$

$$\mathrm{MAE}\left(m,n_1\right) \overset{\text{def}}{=} n_1^{-1}\sum\nolimits_{t=n_0+1}^{n}\left|\hat{\epsilon}_t^{m}\right| \tag{1}$$

In the results tables, we report relative performance metrics, calculated as the ratio of each model's MSE or MAE to the corresponding measure obtained from a benchmark model that uses the sample mean as the forecast.

4. Methodology

This study implements a rolling-window Quantile Regression (QR) and Ordinary Least Squares (LS) approach to forecast[2] the monthly growth rate of the energy consumption index, denoted as ENI_t. The purpose is to examine how lagged values of newly introduced indices affect the predictive power of the energy consumption variable. The analysis covers a rolling sample of data, allowing the forecasting model to adapt over time.

Let y_t be our dependent variable defined as: $y_t = \log\left(\mathrm{ENI}_T/\mathrm{ENI}_{t-12}\right)$, where ENI represents the energy consumption index at time *t*, and ENI_{t-12} corresponds to its value 12 months earlier. This transformation captures the annualized growth rate of ENI, ensuring comparability across time periods while accounting for seasonal variations: For our analysis, we consider five energy-related time series: industrial production (IND_t), global price of Brent Crude (BRE_t), deep-sea freight transportation (SET_t), air transportation (ART_t), and motor vehicle equipment (VET_t). We selected Brent crude oil, industrial production, and transportation indices based on their direct and empirically validated influence on energy consumption and prices. Industrial production is a proxy for broad economic activity and energy demand (Kilian, 2009). Crude oil prices affect energy costs through fuel pass-through effects (Baumeister & Peersman, 2013). Transportation variables—sea, air, and vehicle—represent highly energy-intensive sectors with strong

[2]For other methodological contributions you can refer to Guerard et al. (2024), Kyriazi and Thomakos (2020a, 2020b), and Kyriazi (2024).

links to demand-side price pressure. To normalize the variables, we start by scaling each series relative to its initial observation, converting each value into a ratio of that starting point. We then compute the growth rates by taking the seasonal difference of their logarithms. This transformation promotes stationarity and facilitates a clearer interpretation of the data. The resulting variables serve as explanatory inputs in the forecasting exercise.

To continue with our forecast exercise, we construct three composite indices from normalized levels of the original variables. The first index I_{t1} is constructed as a composite indicator that aggregates five standardized level series–obtained from the previous step: IN_t, BR_t, SE_t, AR_t, and VE_t. The index is defined as a simple arithmetic average:

$$I_{t1} = \frac{1}{5}\left(\mathrm{IN}_t + \mathrm{BR}_t + \mathrm{SE}_t + \mathrm{AR}_t + \mathrm{VE}_t\right)$$

This formulation imposes equal weights on each component under the assumption that each series contributes symmetrically to the underlying latent construct. In this context, the first index mitigates multicollinearity by summarizing information from several correlated predictors into a single regressor. It reduces dimensionality—particularly valuable in forecasting settings with limited sample sizes or rolling windows—and captures common co-movements among the constituent series, effectively serving as a proxy for an underlying latent factor.

The second index I_{t2} is defined as the equally weighted average of the standardized series BR_t, SE_t, AR_t, and VE_t, each receiving a weight of 0.25:

$$I_{t2} = \frac{1}{4}\left(\mathrm{BR}_t + \mathrm{SE}_t + \mathrm{AR}_t + \mathrm{VE}_t\right)$$

reflecting their joint influence on the broader energy-related transportation environment. By excluding industrial production (IN), this index focuses specifically on the mobility and fuel-related dimensions of economic activity, serving as a proxy for transportation-linked energy demand[3].

The third index, denoted as I_{t3}, is constructed to reflect the relative intensity of sea transportation in comparison to air and vehicle transportation combined. It is defined as:

$$I_{t3} = \frac{\mathrm{SE}_t}{\mathrm{AR}_t + \mathrm{VE}_t}$$

where SE denotes the sea transportation index, AR the air transportation index, and VE the vehicle transportation index. This ratio serves as an indicator of modal substitution effects, capturing the extent to which maritime transport dominates or lags behind other transport modes in the energy-related transportation sector.

We construct a comprehensive forecasting model that incorporates all explan-

[3]The equal weighting scheme was chosen for transparency and to avoid overfitting given the sample size. While this imposes symmetry, it reflects the assumption that each indicator carries comparable predictive information.

atory variables and falls within the class of ARDLX models. Specifically, we consider the following formulation:

$$y_t = \beta_0 + \sum_{i=1}^{2}\beta_i y_{t-i} + \sum_{i=1}^{2}\gamma_i x_{t-i,1} + \sum_{i=1}^{2}\delta_i x_{t-i,2} + \sum_{i=1}^{2}\theta_i x_{t-i,3} + \varepsilon_t \tag{2}$$

where:

- y_t denotes our dependent variable using both LS and QR techniques.
- y_{t-i} represents the i-th lag of the dependent variable. In our specification, we include two lags to capture potential autoregressive dynamics.
- $x_{t-i,1}$ corresponds to the i-th lag of the first composite index, with $i = 1, 2$.
- $x_{t-i,2}$ denotes the i-th lag of the second index with $i = 1, 2$.
- $x_{t-i,3}$ represents the i-th lag of the third index with $i = 1, 2$.

The choice of two lags for all variables is based on a combination of empirical precedent and preliminary model selection using the Bayesian Information Criterion (BIC). This lag structure captures short-term dynamics without overfitting and is consistent with prior ARDL literature in macroeconomic forecasting (Baumeister & Kilian, 2015). Our empirical exercise then proceeds as follows: We estimate the parameters of our models, including the AR(1) and AR(2) traditional benchmark models, using both LS and QR approaches. For the estimation of the models, we also use rolling windows of 36, 40, and 60 months. Once the models are estimated, we generate forecasts and repeat this process iteratively until the full dataset has been utilized. We then evaluate our forecasts by applying the widely used measures of mean absolute error and mean squared error, highlighting the top-performing models across all different combinations.

5. Discussion of Results

In this section, we present the results of our empirical exercise across four distinct time periods: 1993:12-2025:3, 2000:12-2025:3, 2004:12-2025:3 and 2008:12-2025:3. Our findings are illustrated in the following four tables that include the newly introduced indices used to evaluate the forecasting models. The estimation is carried out exclusively via rolling windows, with adequate sizes of 36, 40 and 60 observations, in order to maintain dynamic monitoring of the evolution of the forecast over time. We use the AR(1) and AR(2) models as our benchmark models to evaluate the performance of our newly introduced indices: AEI-ARDLX(2, 2), TEI-ARDLX(2, 2), and MTI-ARDLX(2, 2). All models are evaluated using the Quantile Regression and Ordinary Least Squares methods. For evaluating the predictions, two key metrics are used that facilitate direct comparison of the relative Mean Squared Error (MSE) and the relative Mean Absolute Error (MAE).

Initially, the AR(1) and AR(2) models serve as benchmark models for comparison purposes. The AEI-ARDLX(2, 2) model, one of the three novel specifications we test, incorporates all five independent variables with equal weighting for forecasting purposes. The second model, TEI-ARDLX(2, 2), uses equal weights for the four independent variables (excluding INDPRO) and focuses on the transport sector. Finally, the MTI-ARDLX(2, 2) specification incorporates a mobility energy intensity ratio, defined as the share of sea transportation (SE) relative to the combined transportation of air and vehicle equipment (AR + VE), designed to reflect structural shifts in transport modal efficiency. A thorough analysis of the performance by period with a benchmark comparison of the three models in both MAE and MSE terms is presented below.

Table 1. Forecast performance of AR and ARDLX models with composite indicators: relative MSE and MAE (1993:12-2025:3).

	Models	QR	Roll	QQ	LS	Roll
Relative MSE	AR(1)	0.130	40	0.5	0.130	36
	AR(2)	0.124	40	0.5	0.117	40
	AEI-ARDLX(2, 2)	0.082	40	0.5	0.085	40
	TEI-ARDLX(2, 2)	0.090	60	0.5	0.092	40
	MTI-ARDLX(2, 2)	0.099	60	0.5	0.097	36
Relative MAE	AR(1)	0.322	40	0.5	0.320	36
	AR(2)	0.330	40	0.5	0.345	60
	AEI-ARDLX(2, 2)	0.269	40	0.5	0.275	40
	TEI-ARDLX(2, 2)	0.282	40	0.5	0.284	40
	MTI-ARDLX(2, 2)	0.298	60	0.5	0.288	36

LS and QR columns show relative MSE and MAE, computed as the ratio to the sample mean forecast. Roll is the rolling window size used in the estimation. QQ corresponds to the quantile that yields optimal forecasting performance. The forecasting models correspond to those specified in Equation (2).

The results of the study demonstrate that ARDLX-based models exhibit improved accuracy over the conventional benchmarks in both the QR and LS methodologies, in terms of MSE and MAE, for the initial period in Table 1 (1993:12-2025:3). The AEI-ARDLX(2, 2) model exhibits optimal performance with a relative MSE of 0.082 in the QR method and 0.085 in the LS method, utilizing a rolling window of 40 observations. In concrete terms, AEI-ARDLX(2, 2) model consistently yields lower forecast errors than both benchmark models, particularly under QR, where improvements reach up to 59% over the AR(1) and 51% compared to the AR(2) and from 36% to 53% in the LS method, respectively. Subsequently, in terms of relative MAE, the AEI-ARDLX(2, 2) model preserves its superiority over the benchmarks, demonstrating explicitly better efficiency among the ARDLX-based models. Specifically, the relative MAE value of 0.269 for the QR method exceeds that of traditional benchmark models by 20% to 23% accordingly. Furthermore, in terms of MAE, the AEI-ARDLX(2, 2) model demonstrates its superiority over the conventional benchmarks by 16% to 25% in the LS method, respectively. The results of the other two ARDLX-based models are also important, as they consistently outperform over the benchmarks. We observe that the TEI-ARDLX(2, 2) model outperforms the benchmark models in terms of MSE under the QR method, achieving a 44% improvement over AR(1) and a 38% improvement over AR(2) with a rolling window of 60 observations. Similarly, under the LS method and utilizing a 40-observation window, the TEI-ARDLX(2, 2) model shows a 41% improvement over AR(1) and a 27% improvement compared to AR(2). Likewise, in relative MAE terms, the TEI-ARDLX(2, 2) model also outperforms the conventional benchmarks in the QR method by 14% to 17% and 13% to 21% in the LS method, using a 40-observation window. MTI-ARDLX(2, 2) maintains a remarkable lead over the benchmarks with an improved yield ranging from 34% over the AR(1) in the LS method, in terms of MSE, to 8% over AR(1) in the QR method, in MAE terms. It is notable that the relative MSE prediction measure shows enhanced returns across the set of models.

As illustrated in Table 2: 2000:12-2025:3, the performance of the ARDLX-based models is further enhanced during this period. The AEI-ARDLX(2, 2) and TEI-ARDLX(2, 2) models once again exhibit the lowest relative MSE (0.081) using a 40-observation rolling window and (0.088) using a 60-observation rolling window. The MTI-ARDLX(2, 2) model follows with an MSE of 0.095 utilizing a 60-observation window, consistently confirming the superiority of the models over the traditional benchmark models with differences ranging between 26% and 62% for both the QR and LS methods. In terms of MAE, the performance of the ARDLX-based models is similar for both the QR and the LS methods. However, the prediction measures are slightly lower, yet the ARDLX-based models still outperform the benchmarks with a better performance ranging from 7% to 21%.

Table 2. Forecast performance of AR and ARDLX models with composite indicators: relative MSE and MAE (2000:12-2025:3).

	Models	QR	Roll	QQ	LS	Roll
Relative MSE	AR(1)	0.131	40	0.5	0.134	40
	AR(2)	0.120	60	0.5	0.116	40
	AEI-ARDLX(2, 2)	0.081	40	0.5	0.085	40
	TEI-ARDLX(2, 2)	0.088	60	0.5	0.091	60
	MTI-ARDLX(2, 2)	0.095	60	0.5	0.092	60
Relative MAE	AR(1)	0.318	40	0.5	0.321	36
	AR(2)	0.328	40	0.5	0.321	40
	AEI-ARDLX(2, 2)	0.270	40	0.5	0.278	40
	TEI-ARDLX(2, 2)	0.286	40	0.5	0.288	40
	MTI-ARDLX(2, 2)	0.298	60	0.5	0.295	40

LS and QR columns show relative MSE and MAE, computed as the ratio to the sample mean forecast. Roll is the rolling window size used in the estimation. QQ corresponds to the quantile that yields optimal forecasting performance. The forecasting models correspond to those specified in Equation (2).

In the third period displayed in Table 3: 2004:12-2025:3, we observe that the performance of the ARDLX-based models continues to surpass the benchmarks in all performance metrics. In further detail, the performance of the ARDLX-based models exceeds the benchmarks in the QR method in MSE terms within the range of 56% to 22%. In the LS method, both the AEI-ARDLX(2, 2) with a rolling window of 40 observations and the TEI-ARDLX(2, 2) using a 60-observation window consistently outperform the benchmarks by 52% to 24%, in MSE terms, indicating stable performance. Similarly, the MTI-ARDLX(2, 2) model surpassed the conventional benchmarks by a margin of 21% to 34% in terms of MSE, using a rolling window of 60 observations. In terms of MAE, we observe close similarities to Table 2 for both the QR and the LS methods. Furthermore, we note an improvement in performance ranging from 2% to 20% when employing the QR method and from 7% to 14% when utilising the LS method.

Table 3. Forecast performance of AR and ARDLX models with composite indicators: relative MSE and MAE (2004:12-2025:3).

	Models	QR	Roll	QQ	LS	Roll
Relative MSE	AR(1)	0.106	60	0.5	0.107	60
	AR(2)	0.106	60	0.5	0.097	40
	AEI-ARDLX(2, 2)	0.068	40	0.5	0.070	40
	TEI-ARDLX(2, 2)	0.076	40	0.5	0.078	60
	MTI-ARDLX(2, 2)	0.087	60	0.5	0.080	60
Relative MAE	AR(1)	0.291	40	0.5	0.291	36
	AR(2)	0.297	40	0.5	0.293	40
	AEI-ARDLX(2, 2)	0.248	40	0.5	0.256	40
	TEI-ARDLX(2, 2)	0.262	40	0.5	0.267	40
	MTI-ARDLX(2, 2)	0.286	60	0.5	0.271	36

LS and QR columns show relative MSE and MAE, computed as the ratio to the sample mean forecast. Roll is the rolling window size used in the estimation. QQ corresponds to the quantile that yields optimal forecasting performance. The forecasting models correspond to those specified in Equation (2).

In the final period, as demonstrated in Table 4: 2008:12-2025:3, we perceive that the ARDLX-based models continue to exhibit superior performance in terms of both MSE and MAE to the established benchmarks. A more detailed investigation reveals that the AEI-ARDLX model continues to exhibit superior performance compared to the traditional benchmarks utilizing the QR method, by 32% and using the LS by 29% to 32%, in terms of relative MSE. Furthermore, in MAE terms, we observe performance enhancements of all the ARDLX-based models in comparison to the traditional benchmarks, ranging from 9% to 12% increase using the LS method, and improvements ranging from 1% to 16% using the QR method.

Overall, we conclude that the results demonstrate a stable pattern of ARDLX-based models outperforming the benchmarks across periods when utilizing the QR method in relative MSE terms. In a similar pattern, the outcomes derived from the LS method manifest a less robust pattern in terms of MAE compared to the QR method. The superior performance of the AEI-ARDLX(2, 2) model likely reflects the advantage of equal weighting. The TEI-ARDLX(2, 2) model is followed in terms of improved performance against benchmarks, with the INDPRO indicator excluded and the same weight applied to the remaining four indicators. Moreover, the MTI-ARDLX(2, 2) model, which is a mobility ratio, demonstrates relatively weaker performance in comparison to the other two models, yet it surpasses the traditional benchmarks.

Table 4. Forecast performance of AR and ARDLX-based models with composite indicators: relative MSE and MAE (2008:12-2025:3).

	Models	QR	Roll	QQ	LS	Roll
	AR(1)	0.096	36	0.5	0.095	36
	AR(2)	0.096	60	0.5	0.093	40
Relative MSE	AEI-ARDLX(2, 2)	0.073	40	0.5	0.072	40
	TEI-ARDLX(2, 2)	0.078	40	0.5	0.076	36
	MTI-ARDLX(2, 2)	0.088	36	0.5	0.077	60
	AR(1)	0.280	36	0.5	0.280	36
	AR(2)	0.294	36	0.5	0.286	36
Relative MAE	AEI-ARDLX(2, 2)	0.254	40	0.5	0.256	40
	TEI-ARDLX(2, 2)	0.261	40	0.5	0.256	36
	MTI-ARDLX(2, 2)	0.277	36	0.5	0.257	36

LS and QR columns show relative MSE and MAE, computed as the ratio to the sample mean forecast. Roll is the rolling window size used in the estimation. QQ corresponds to the quantile that yields optimal forecasting performance. The forecasting models correspond to those specified in Equation (2).

6. Conclusion and Policy Implications

In our research, we examine the predictive power of composite indices that combine multiple indicators—such as industrial production, Brent crude oil prices, and maritime, air, and vehicle transportation—to achieve improved forecasting of the Energy Consumer Price Index. We construct three composite indices, which we incorporate into ARDLX models, applying both Quantile Regression (QR) and Least Squares (LS) methods using rolling windows. Our results show that ARDLX-based models consistently outperform traditional benchmark models, AR(1) and AR(2), as well as both estimation methods across all examined forecast periods. The AEI-ARDLX(2, 2) model consistently outperforms the other ARDLX-based models. Moreover, the superiority of all three ARDLX-based models is most pronounced when assessed using relative MSE compared to relative MAE. These forecasting models can inform targeted energy policy interventions. For instance, accurate short-term CPI forecasts could guide the timing of strategic petroleum reserve releases, help design responsive energy subsidies, or support inflation-targeting decisions by central banks. Additionally, transportation-based signals may assist in planning for fuel supply allocation during high-demand seasons or disruptions.

Our analysis highlights the significance of integrating data related to oil prices, industrial production, and operations in the maritime, air, and road transport sectors.

From a policy perspective, our research demonstrates that energy policy-making benefits from the use of high-frequency leading indicators with strong predictive power. The use of such indicators by competent authorities contributes to the design of targeted interventions, both during periods of stability and in conditions of uncertainty or crisis. Future research could explore the integration of machine learning techniques—such as LSTM or ensemble methods—to capture potential nonlinearities and enhance predictive accuracy. This would complement the existing framework and provide a broader toolkit for energy policy planning and economic forecasting. Overall, our study proposes a practical and robust approach to forecasting the Energy Consumer Price Index, with direct applications in energy and macroeconomic policy-making.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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