IJEEP

INTERNATIONAL JOURNAL OF ENERGY ECONOMICS AND POLICY

EJ EconJournals

ISSN: 2146-4553

International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2026, 16(2), 485-493.

EJ EconJournals

Insight between Energy Factors and Digitalization on Road Freight Volume: Evidence from Kazakhstan

Dias Koshetayev[1], Dinara Sadykhanova[1], Arman Seisenbekov[1], Zauresh Akhmetova[1]*, Anastasiya Lukina[2]

[1]Al-Farabi Kazakh National University, Almaty, Kazakhstan, [2]Peoples' Friendship University of Russia named after Patrice Lumumba, Moscow, Russia. *Email: akhmetovazauresh13@gmail.com

Received: 19 October 2025 **Accepted:** 25 January 2026 **DOI:** https://doi.org/10.32479/ijeep.22812

ABSTRACT

Geopolitical instability in the world has a strong impact on energy prices and international relations. For Kazakhstan, which does not have direct access to the open ocean, freight transport by road is one of the main sources of transportation, and as a country connecting Europe and Asia, it is located in a transit environment, and a large number of transit trucks also pass through it daily. In this regard, the study of the impact of energy factors and the level of digitalization, which is currently widely used to optimize freight transport, on the overall transport turnover has become a topical issue. In this regard, the purpose of this research work is to determine the impact of energy factors and digitalization on the turnover of freight transported by road. The following variables, which are not similar to each other, but are closely related both directly and indirectly, were taken at the same time: Automobile cargotunrover (mln tonna-km), Transport consumer price index, Diesel price, Total final energy consumption in thousands of tons of oil equivalent in TRANSPORT, Inflation, Length of internal public roads (km), Carbon dioxide (CO_2) emissions from Transport (Energy) (Mt CO_2e), ICT service exports (BoP, current US$), Fixed broadband subscriptions, Individuals using the Internet (% of population). Due to the complexity of the variables, two Nonlinear Autoregressive Distributed Lag econometric models were created. The model results and a number of useful recommendations are summarized in the Conclusion section.

Keywords: Diesel Price, CO_2 Emissions, Total Final Energy Consumption, Internet Users, Internal Length of Roads
JEL Classifications: L91, Q41, O33

1. INTRODUCTION

An essential part of a nation's energy planning and policy is a thorough grasp of the various sectors' energy demands. Road transportation is vital to society and the vitality of economic activity (Köseoğlu, 2025). Numerous socioeconomic factors, including population, urbanization, industrialization, net capital income, and technological advancement, especially, advancement and implementation of digital technology, all influence energy consumption (Hasanuzzaman et al., 2020; Al-lami et al., 2025). Transportation accounts for 30% of all delivered energy worldwide, making it the second-largest energy-consuming sector behind the industrial sector (Atabani et al., 2011). The use of gasoline and diesel for road transportation is expanding at a higher rate than other sectors, and it looks like this trend will continue to accelerate in the near future (Ong et al., 2012). The transportation industry consumed around 55% of the world's petroleum and liquid fuels in 2012 (Smith and Parmenter, 2016). Road transportation accounted for 73.6% of total energy used in transportation in the EU in 2022, significantly more than air transportation (11.4%), water transportation (13.0%), and rail transportation (1.4%) (Eurostat, 2025). The transportation industry is the most substantial and uses the most fossil fuels worldwide. Due to the fact that every nation depends on logistics, this industry has become the global connective since COVID-19 began in 2019 (Pramuanjaroenkij and Kakaç, 2023). Geopolitical tensions and volatile oil prices have

This Journal is licensed under a Creative Commons Attribution 4.0 International License

had a significant impact on the energy sector and the transportation sector that depends on it (Zheng et al., 2017). Local economic and demographic factors, urban form factors like density and design, and regional traits like polycentricity and opportunity access all affect how much energy is used for local transportation (Kaza, 2020). No nation can function at this stage of development without road freight transportation. This means of transportation is commonly used in modern civilization to convey commodities both locally and abroad. The many benefits that come with road freight transportation are what make it so important (Ragozin, 2024). An efficient economy at the national and international levels is predicated on the growth of transportation (Domagała and Kadłubek, 2023).

Thus, the purpose of this research work is to assess the energy and ancillary factors that influence road freight transportation in Kazakhstan.The paper is structured as follows: Introduction, Literature review, Methodology, Data and Findings, and Conclusion.

2. LITERATURE REVIEW

Road transport is one of the most actively developing sectors (Sładkowski and Turayev, 2024). The road freight industry is fiercely competitive, and transportation expenses make up between 35% and 50% of the entire cost of logistics, both of which help transport companies increase their logistical efficiency. Reducing transportation costs is therefore essential for transportation companies (Shedenov and Askarov, 2018). In 2023, private automobiles and vans accounted for over 10% of energy-related CO_2 emissions and over 25% of the world's oil consumption. Car efficiency would need to increase by 5% annually in order to double the world's annual improvement in energy intensity by 2030 (IEA, 2025). Huge fuel and energy intensity plays important role in pricing of transportation services (Song et al., 2014; Sharapiyeva et al., 2019; Li and Wang, 2025). Fuel prices and fuel use in transportation, or energy efficiency, have a significant impact on transportation expenses (Milewski and Milewska, 2023). The optimally formed volume of cargo transportation, achieved via the use of several forecast models based on the collection and analysis of pertinent indicators (factors) that influence the desired indicator, is a necessary condition for the ongoing and efficient operation of the logistics process (Ragozin, 2024). Road transport can most fully satisfy the needs of the customers since it adheres to its timetable, which is set by agreement between the contractor and the customer (without referring to station, airport, or port schedules, for example) (Chatti, 2021). Individual cost components are determined by the vehicle's worth, the allowable total weight, the engine type, and the fuel (Jacyna and Wasiak, 2015). Although electrifying heavy-duty vehicles is a huge challenge because of the high technical requirements and cost competitiveness, low-carbon road freight transport is essential to reducing global warming (Link et al., 2024). There are several methods to determine the fuel consumption of a vehicle. First, there is the consumption specified by the manufacturer, but this value is often obtained only under ideal road conditions. Additionally, some software programs calculate fuel consumption using an incorrect formula that suggests a 24% consumption for an empty truck and an additional 0.5% for each ton loaded. In the case of grain transport, where the mass of the load is approximately 24 tons, the consumption of a truck is 36%, plus or minus 0.5% (Iamandii et al., 2025). By examining the various categories of the aggregate consumer price index (CPI), the authors examined how changes in domestic fuel prices affected consumer price inflation. They discovered the following: Compared to industrialized economies, the inflation response to shocks to the price of gasoline is less but more widespread and persistent in developing economies. Second, we demonstrate that previous research that estimated the pass-through to inflation using crude oil prices rather than retail fuel prices greatly underestimated it. Third, the distributional effect is progressive even though all households' purchasing power decreases as gasoline prices rise (Kpodar and Liu, 2022).

Franco (2014) looked at how the Vellore district's rising vehicle density was affecting emissions and energy usage. The results showed that the growth of automobiles also increased CO_2 emissions. Rasool et al. (2019) used an autoregressive distributive lag model to investigate how population density, economic growth, oil prices, and the energy intensity of road transport affect Pakistan's transportation sector's carbon dioxide (CO_2) emissions. According to study results, rising energy intensity, population density, and road infrastructure raise CO_2 emissions in the transportation sector, whereas fuel prices and economic expansion lower CO_2 emissions. The subject of whether the economy (GDP and exports and imports) and energy costs (crude oil and diesel) have an impact on road and rail transport in Poland was investigated by Przekota and Szczepańska-Przekota (2024). Results indicated that rail travel is positively affected by changes in fuel prices, yet the basic energy resource employed in rail transport is not gasoline but electricity. Haxhimusa and Liebensteiner (2025) claim that higher fuel prices encourage electric/hybrid adoption, decrease traditional automobile purchases. Gasoline price is a crucial modifier of interventions' effectiveness but largely in context where infrastructures are accessible (Chevance et al., 2024). Zou and Chau (2019) evaluated the long- and short-run effects of fuel prices on freight volumes in various forms of transportation in Shanghai. Irrespective of either in the short- or long-run, real fuel prices had no impact on freight transportation volumes. However, authors discovered a Granger causation going from rail to road freight, whereby in the short-run (1 month), a 1% change in rail freight would lead to a loss of 0.07% in road freight.

In addition, due to the widespread use of digital technologies and the Internet, these factors are also having an impact on the movement of goods by road. For instance, according to Wang et al. (2025) the level of supply chain digitization can boost industrial businesses' competitiveness; logistics effectiveness can help businesses become more competitive; the relationship between industrial businesses' competitiveness and logistical efficiency is positively moderated by environmental legislation. Khamdamov et al. (2025) claim that digital platforms promote freight operations by cutting down on journey times, improving route management, and automating cargo handling procedures.

As one of the main economic sectors in Kazakhstan, the transportation and logistics industry supports the prosperity and well-being of the country (Assanova and Jaroslaw, 2025; Zhumanov et al., 2024; Ayaganova, 2024). For Kazakhstan, which has no direct access to the world water ways, road and rail freight transport play a highly vital role, and logistical ties between neighboring nations have not only economic, but also political weight (Bodaubayeva et al., 2024). Even though Kazakhstan has spent $35 billion on this industry over the previous 15 years, projections indicate that the country's transportation and logistics sector will account for 9% of its GDP by 2025, up from 6.2% in 2022 (Saktaganova et al., 2024). Three refineries in Kazakhstan provide finished oil products. However, there is a considerable demand for gasoline and diesel due to the ongoing growth in transit freight traffic. The price increase has also been made worse by Kazakhstan's erratic inflation. The energy sector's fixed asset depreciation ranges from 60% to 70%. Additionally, there is a dearth of investment inflow, which lowers thermal efficiency, raises logistics costs for the delivery of energy raw materials, deteriorates the environment, and stops the nation's economy from developing further (Nurgaliuly and Smagulova, 2025). Also, the expansion of the transportation and logistical complex is mostly constrained by low levels of information and digital technologies as well as high levels of physical and moral deterioration of the majority of the infrastructure (Polukhina and Mizanbekova, 2022). It is evident that road traffic has an impact on CO_2 emissions for Kazakhstan, which has set itself the goal of adopting sustainable development goals (Dildebayeva et al., 2025; Kakizhanova et al., 2024). Road freight transportation will continue to be important for a very long time since electric vehicles cannot travel very far. The demand for gasoline and diesel is continuously rising due to the increase in domestic cargo turnover and the purchase of fuel as "reserve" by transit carriers. For instance, The Republic of Kazakhstan's transportation system carried 3944.8 million tons of freight in 2020. Road transport accounted for 83% (3287 million tons) of the total volume of products transported, followed by railways at 10% (402.3 million tons), pipelines at 6.5% (253.7 million tons), and other modes of transportation at <1% (Aitkaliyeva et al., 2021).

3. METHODS

Taking into account the results of the reviews in the previous section, we examine the relationship between AutoCar and explanatory factors in the Republic of Kazakhstan for the period 2003-2023. In this case, AutoCar is defined by the following equation:

$$AutoCar = f\,(TCPI, DP, TFEC, inf, LIPR, CO2E, ICTE, FBS, IUI) \quad (1)$$

Where all of their definitions and measurements are given in the Table 1.

Table 1: Model variables and sources

Variables	Definitions	Sources
AutoCar	Automobile cargotunrover (mln tonna-km)	Bureau of National Statistics of RK
TCPI	Transport consumer price index	Bureau of National Statistics of RK
DP	Diesel price (тп/д)	Globalpetrolprices.com
TFEC	Total final energy consumption in thousands of tons of oil equivalent in TRANSPORT	World development indicators (WDI)
inf	Inflation, %	World development indicators (WDI)
LIPR	Lenth of internal public roads (km)	Bureau of National Statistics of RK
CO2E	Carbon dioxide (CO_2) emissions from transport (energy) (Mt CO_2e)	World development indicators (WDI)
ICTE	ICT service exports (BoP, current US$)	World development indicators (WDI)
FBS	Fixed broadband subscriptions	World development indicators (WDI)
IUI	Individuals using the Internet (% of population)	World development indicators (WDI)

Source: Authors

he ADF test revealed that all variables were stationary at the I(0) or first difference I(1) levels (Table 2), except for the first difference without Intercept and trend. Therefore, two nonlinear models were estimated for this case. ARDL methodology was also used to conduct long- and short-run analyses of the relationships between variables. The order of integration of variables was first considered to determine the suitability of the ARDL model for the study, and a special test was used to select a maximum of one lag (Table 3).

NARDL1-2 nonlinear models were estimated using the logarithm of AutoCar and first differences, respectively, and long- and short-run analyses of the relationships between variables were conducted. In NARDL1-2 nonlinear distributed-lag autoregressive models, the procedure determines the presence of cointegration between the sample variables. The bounds test examines long-run relationships, and the results of the boundedness test are presented in Table 4.

Two main models were constructed. In the NARDL1 model, the linear specification was transformed into a logarithmic specification, and in NARDL2, a semi-logarithmic specification.

Thus, NARDL1 power-law model structure 1 is expressed in form 2:

$$\begin{aligned}
LOG\left(AutoCar_t\right) = \beta_0 + \sum_{k=1}^{m}\beta_1 LOG\left(AutoCar_{t-k}\right) + \\
\sum_{k=0}^{n}\beta_2 LOG(LIPR_{t-k}) + + \sum_{k=0}^{p}\beta_3 LOG(CO2E_{t-k}) \\
+ \sum_{k=0}^{q}\beta_4 LOG(IUI_{t-k}) + \sum_{k=0}^{r}\beta_5 LOG(TFEC_{t-k}) \\
+ + \gamma_0 LOG(AutoCar_{t-i}) + \gamma_1 LOG(LIPR_{t-i}) \\
+ \gamma_2 LOG(CO2E_{t-i}) + \gamma_3 LOG(IUI_{t-i}) \\
+ \gamma_4 LOG\left(TFEC_{t-i}\right) + \varepsilon_t \qquad (2)
\end{aligned}$$

Where, operator Δ represents the differencing operation.

And the NARDL2 exponential model 2 structure is expressed in equation 3:

Table 2: ADF unit root tests

Variables	Intercept			Trend and intercept			None		
	Level	First difference	Order of integration	Level	First difference	Order of integration	Level	First difference	Order of integration
AutoCar	−1.720 (0.407)	−4.21*** (0.005)	I (1)	−1.852 (0.641)	−4.12** (0.022)	I (1)	−0.975 (0.287)	−4.330*** (0.000)	I (1)
TCPI	−4.00*** (0.007)	−5.76*** (0.000)	I (0)	−4.07*** (0.023)	−3.569* (0.068)	I (0)	−0.222 (0.594)	−5.92*** (0.000)	I (1)
DP	2.004 (0.888)	−2.525 (0.126)	>I (1)	0.074 (0.994)	−2.992 (0.160)	>I (1)	4.833 (1.000)	−1.547* (0.0917)	I (1)
TFEC	2.183 (0.999)	−4.137* (0.0053)	I (1)	0.913 (0.999)	−4.739* (0.007)	I (1)	3.234 (0.999)	−0.338** (0.007)	I (1)
inf	−2.776* (0.080)	−5.56*** (0.000)	I (0)	−2.738 (0.233)	−5.47*** (0.002)	I (1)	−0.433 (0.514)	−5.636*** (0.000)	I (1)
LIPR	−1.389 (0.563)	−3.601 (1.000)	>I (1)	4.229 (1.000)	2.825 (1.000)	>I (1)	−1.589 (0.104)	−3.619*** (0.001)	I (1)
CO2E	−0.040 (0.952)	−5.72*** (0.000)	I (1)	−1.977 (0.578)	−5.74** (0.001)	I (1)	2.453 (0.995)	−4.179*** (0.0003)	I (1)
ICTE	4.631 (1.000)	−0.315 (0.905)	>I (1)	3.155 (1.000)	−0.988 (0.922)	>I (1)	1.250 (0.940)	−0.018 (0.096)	I (1)
FBS	−0.656 (0.836)	−2.497 (0.617)	>I (1)	−1.892 (0.617)	−2.531 (0.311)	>I (1)	−0.223 (0.592)	−1.530* (0.095)	I (1)
IUI	−1.337 (0.589)	−2.639 (0.104)	>I (1)	−2.383 (0.375)	−2.722 (0.240)	>I (1)	−0.048*.(0.654)	−1.281* (0.097)	I (1)

1) *, **, *** denote statistically significant at the 10%, 5% and 1% levels, respectively. P-value is inside brackets

$$LOG(AutoCar_t) = \beta_0 + \sum_{k=1}^{m}\beta_1 LOG(AutoCar_{t-k}) + \sum_{k=0}^{n}\beta_2 TCPI_{t-k} + \sum_{k=0}^{p}\beta_3 DP_{t-k} + \sum_{k=0}^{q}\beta_4 Inf_{t-k} + \sum_{k=0}^{r}\beta_5 ICTE_{t-k} + \sum_{k=0}^{s}\beta_6 FBS_{t-k} + +\gamma_0 LOG(AutoCar_{t-i}) + \gamma_1 TCPI_{t-i} + \gamma_2 DP_{t-i} + \gamma_3 Inf_{t-i} + \gamma_4 ICTE_{t-i} + \gamma_5 FBS_{t-i} + \varepsilon_t \quad (3)$$

4. DATA AND FINDINGS

4.1. Data

This study examines the impact of key factors on the automotive sector in the Republic of Kazakhstan. The study uses data from 2003 to 2023, obtained from national and international databases, as shown in Table 1. The explanatory variables in this study include TCPI, DP, TFEC, inf, LIPR, CO2E, ICTE, FBS, and IUI.

Definitions and measurements of all indicators are given in Table 1 below.

The dynamic change of all indicators presented in the table in the period 2003-2023 is depicted in the following graph:

From the analysis of the graph presented in Graph 1, it is clear that the variables under study are suitable for analysis because the graph shows obvious, consistent and stable time patterns.

4.2. Descriptive Statistics

In this study, descriptive statistics and the NARDL1-2 models were used to test the hypothesis. Descriptive statistics provide insight into various aspects of the dataset. The descriptive statistics results, presented in Table 5, show pooled means, such as the median and mean, as well as measures of variation and spread, such as the standard deviation, maximum, minimum, Jarque-Bera statistic, and skewness, for each variable used in our model.

According to descriptive statistics, for the AutoCar indicator, the mean is 31,794.7 million ton-km, the median is 30,005.4 million ton-km, and the standard deviation is 18,130.8 million ton-km, indicating relatively stable values. The Jarque-Bera statistic is 1.9, and the probability of association is 0.4, which is >0.05, indicating that the series is uniformly distributed. The standard deviation for all indicators except TFEC and ICTE exceeds 0.10. Table 5 shows that for all indicators except LIPR, FBS, and IUI, the skewness coefficient is >0, indicating that they are right-skewed. The kurtosis value for all indicators indicates that the distribution is nearly normal, without excessive kurtosis.

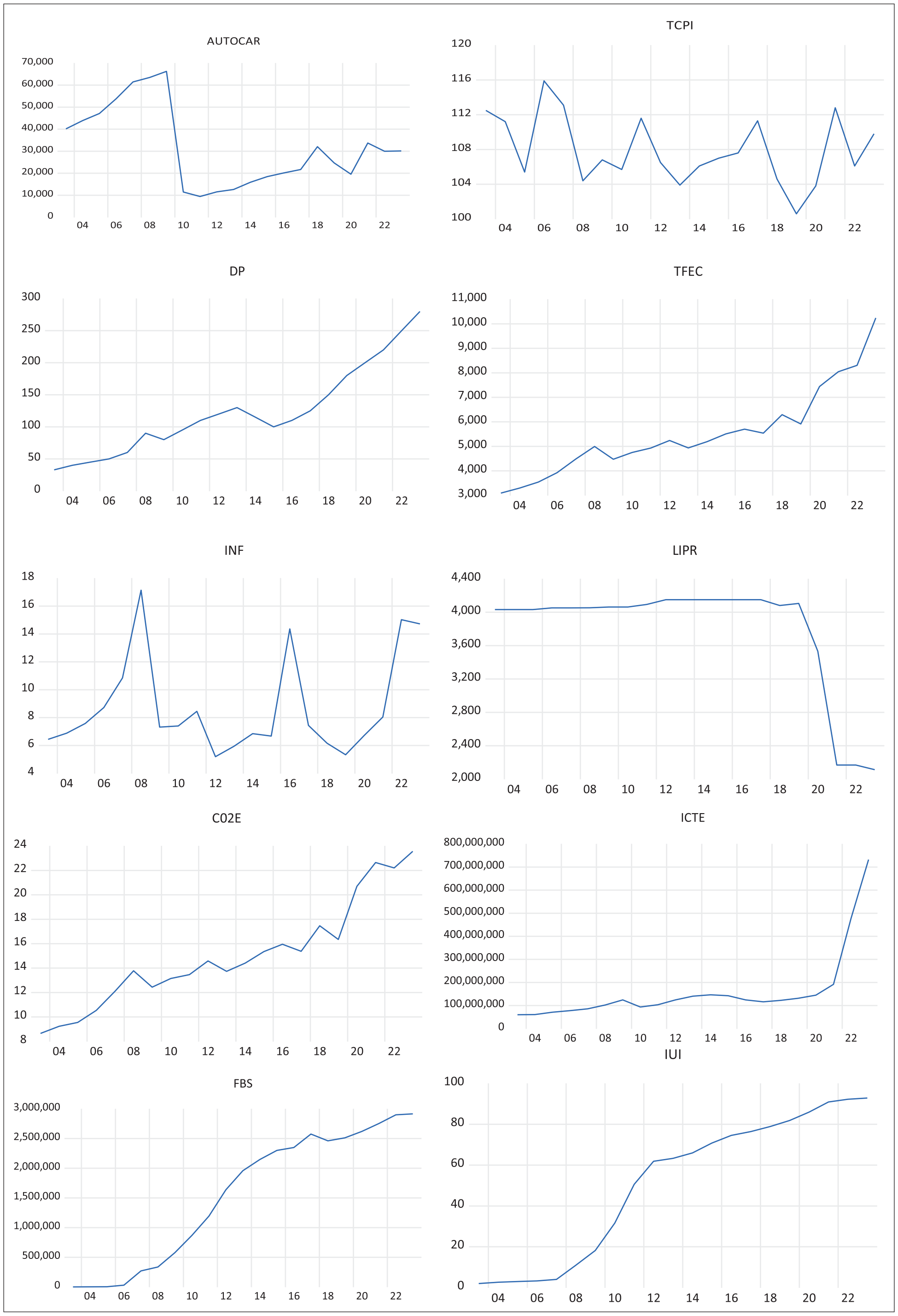
4.3. Unit Root Test

Before examining long-run relationships between series, it is necessary to determine whether they are stationary. To test the

Table 3: Selection order criteria

NARDL1 estimationΔLOG (AUTOCAR)						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	−13.95519	NA	4.58e−06	1.895519	2.144452	1.944113
1	81.34050	133.4140*	4.46e−09*	−5.134050*	−3.640451*	−4.842484*
NARDL2 estimationΔLOG (AUTOCAR)						
Lag	**LogL**	**LR**	**FPE**	**AIC**	**SC**	**HQ**
0	−914.9451	NA	3.99e+32	92.09451	92.39323	92.15282
1	−796.4733	154.0133*	1.26e+29*	83.84733*	85.93837*	84.25552*

Graph 1: Evolution of all variables for Kazakhstan (2003-2023)



Source: Authors

stationarity of the levels or differences of time series variables, augmented Dickey-Fuller (ADF) unit root tests were used. Some variables can be used at the I(0) level, while other variables should be stationary at the first difference I(1).

As shown in Table 2, the ADF results show that most of the study series are not stationary at the Level. However, only in the case of 1st difference without Intercept and trend, all variables are stationary (are stationary at the first difference). Therefore, the ARDL cointegration methodology is the best way to estimate or test the long-run relationship between study variables.

Table 4: Results of cointegration test

Model	F statistics	Critical bounds I (1)	Decision
NARDL1 (1, 0, 1, 0, 0)	8.671929***	3.01-4.44	Cointegration
NARDL2 (1, 1, 1, 1, 0, 1)	6.824601***	2.93-4.21	Cointegration

Critical bounds are reported at 1% (***) and 10% (**) level of significance

The unit root results are consistent with the main assumptions that require the use of the ARDL model test to confirm the existence of long-run relationships between Kazakhstani AutoCar and the significant explanatory factors proposed in the study.

4.4. Lag Selection Criteria

The ARDL bounds testing procedure is used in this study to examine the long-run relationship between TCPI, DP, TFEC, Inf, LIPR, CO_2E, ICTE, FBS, IUI, and AUTOCAR in the Republic of Kazakhstan. NARDL1 models were selected to examine the long-run relationship between the logarithms of the variables under consideration and ΔLOG(AUTOCAR), and NARDL 2 models were selected to examine the relationship between the variables and ΔLOG(AUTOCAR). Before conducting the cointegration test, it is important to determine the lag length criterion. The lag length criterion is determined based on LR, FPE, AIC, SC, and HQ. Table 3 presents the results of the selected lag. As can be seen from Table 6, the selected lag length is 1, since it has more stars and was used throughout the study.

Table 5: Values of descriptive statistics of the displayed series

Values	AutoCar	TCPI	DP	TFEC	Inf	LIPR	CO_2E	ICTE	FBS	IUI
Mean	31794.7	107.9	123	5516.9	8.7	3788.2	15.0	1.61E+08	1543801	50.6
Median	30005.4	106.8	110	5191.5	7.4	4062.9	14.4	1.24E+08	1958820	63.3
Maximum	66253.7	115.9	280.0	10239	17.1	4150.9	23.6	7.32E+08	2916490	92.9
Minimum	9438.5	100.6	33.0	3092.2	5.2	2113.3	8.7	60020092	998.0	2.0
Standard deviation	18130.8	3.9	69.0	1762.0	3.5	697.2	4.3	1.56E+08	1117387	35.1
Skewness	0.6	0.3	0.8	1.0	1.3	−1.9	0.6	2.863918	−0.3	−0.3
Kurtosis	2.1	2.2	2.8	3.8	3.2	4.8	2.5	10.28914	1.4	1.5
Jarque-Bera	1.9	0.8	2.1	4.3	5.6	15.8	1.3	75.19716	2.4	2.5
Probability	0.4	0.7	0.3	0.1	0.1	0.0	0.5	0.000000	0.3	0.3
Sum	667689.2	2266.7	2583	115855	183.3	79551.3	315	3.38E+09	32419815	1062
Sum Sq. deviation	6.57E+09	306.8	95180	62095661	248.7	9720498	373	4.89E+17	2.50E+13	24678

Table 6: Results of NARDL1 and NARDL2 estimation (2003-2023)

Model 1- results of NARDL1 estimationΔLOG (AUTOCAR)			Model 2- results of NARDL2 estimationΔLOG (AUTOCAR)		
Variable	Coefficient	t-statistic (probability)	Variable	Coefficient	t-statistic (probability)
Short run					
LOG (AUTOCAR[−1])	−1.0380***	−6.33561	LOG (AUTOCAR(−1))	−0.8588***	−5.781690
LOG (LIPR)	1.8218***	3.674721	TCPI(−1)	0.0742***	5.548775
LOG (CO_2E[−1])	8.7128***	4.198393	DP(−1)	0.0160***	3.445921
LOG (IUI)	−1.2579***	−5.69596	INF(−1)	0.1130***	3.228422
LOG (TFEC)	−2.7086**	−2.82097	ICTE	−3.7E−9***	−3.282391
ΔLOG (CO_2E)	4.2457**	2.88469	FBS(−1)	−5.5E−07**	−3.073630
			Δ(TCPI)	0.0138	0.992667
			Δ(DP)	−0.01280*	−2.158092
			Δ(INF)	0.0328	1.330743
			Δ(FBS)	−3.4E−6***	−5.186454
Long run					
LOG (LIPR)	1.7552***	4.081605	TCPI	0.0864***	24.66408
LOG (CO_2E)	8.3942***	4.656306	DP	0.0186***	4.069010
LOG (IUI)	−1.2119***	−8.171409	INF	0.1317***	3.517737
LOG (TFEC)	−2.6096**	−2.881675	ICTE	−4.3E−9***	−3.669461
			FBS	−6.4E−7***	−3.830666
Diagnostic	F-statistics	P-value	Diagnostic	F-statistics	P-value
Serial correlation	1.248211	0.3218	Serial correlation	0.161115	0.8539
Heteroskedasticity	0.723784	0.6383	Heteroskedasticity	1.647204	0.2328
Jarque-Bera	1.090173	0.5798	Jarque-Bera	0.01045	0.9995

1) Coefficients are statistically significant at ***1%, **5%, *10% level of significance. 2) Compiled by the authors

4.5. Results of Long - and Short Run Relationship

The study estimated nonlinear NARDL1-2 models to conduct a long-run and short-run analysis of the relationships between variables. The results are presented in Table 6.

The results of the cointegration F-test for these models (Table 4) show that the resulting F-statistics (8.671929 and 6.824601) exceed the upper bound of 4.44 and 4.21, respectively, and are statistically significant at the 1% significance level. These results demonstrate that the selected variables are cointegrated and, in the Kazakhstani case, a long-run relationship exists between them.

Given that the selected variables are cointegrated in the long run, we can proceed to the next step, which requires estimating the long-run and short-run coefficients. Given that the NARDL1-2 models were estimated using first-difference methods, we can assess how changes in the explanatory variables affect the dependent variable in both the long and short runs.

Table 6 shows that all estimated long-run and short-run coefficients of the selected NARDL1(1, 0, 1, 0, 0) model are significant at the 10% significance level. The coefficient of LOG(LIPR) is positive and significant at the 1% significance level, which confirms the statement that Lenth of internal public roads has a noticeable positive impact on AUTOCAR, with a coefficient of 1.7552, all other things being equal. The CO_2E variable with a positive coefficient of 8.3942 also has a positive impact on AUTOCAR in the long run. IUI and TFEC have a long-run negative impact on ΔLOG(AUTOCAR), the corresponding elasticity coefficients are −1.2119%, −2.6096.

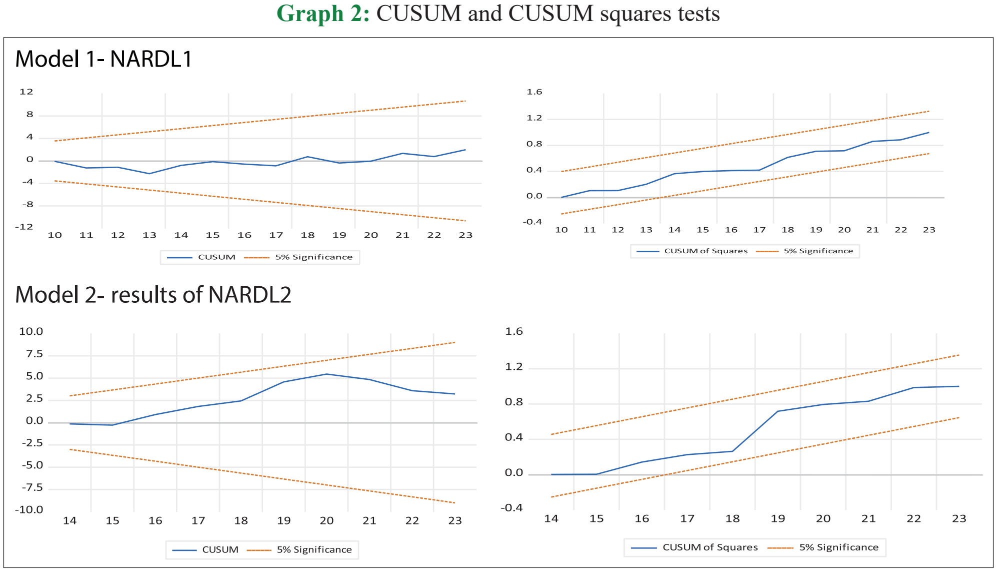
Furthermore, the coefficient of the lagged variable LOG(AUTOCAR[−1]) in period t-1 in the short term was negative (−1.0380) in the short term. All other things being equal, the positive effects of LOG(LIPR), LOG(CO_2E[−1]) and LOG(CO_2E) on ΔLOG(AUTOCAR) were confirmed, with the corresponding coefficients of 1.8218, 8.7128 and 4.2457. The logarithms of the variables LOG(IUI) and LOG(TFEC) correlate negatively with ΔLOG(AUTOCAR) (with coefficients of −1.2579 and −2.7086, respectively) in the short term, which is consistent with the long-term result.

NARDL2(1, 1, 1, 1, 0, 1) estimate. Table 6 presents the empirical results of the Automobile cargotunrover AUTOCAR model. The table shows that the two variables ICTE and FBS have a long-term negative impact on ΔLOG(AUTOCAR), with coefficients of −4.3E−9 and −6.4E−7, respectively. Conversely, the variables TCPI, DP, and INF, with positive coefficients (0.0864, 0.0186, and 0.1317, respectively), have a positive impact on LOG(AUTOCAR) growth in the long run.

Furthermore, the coefficient of the lagged variable LOG (AUTOCAR [−1]) in period t-1 also turned out to be negative in the short run (−0.8588). All other things being equal, the positive impacts of TCPI(−1), DP(−1), and INF(−1) on ΔLOG(AUTOCAR) were confirmed, with coefficients of 0.0742, 0.0160, and 0.1130, respectively. But the change in Δ (DP) negatively affects ΔLOG(AUTOCAR) with a coefficient of −0.01280. ICTE, FBS(−1), Δ (FBS) correlate with ΔLOG(AUTOCAR) negatively (with coefficients of −3.67E−09, −5.5E−07 and −3.4E−6 respectively) in the short term, which is consistent with the long-term result.

Diagnostic Tests were performed to ensure the stability of the nonlinear NARDL1-2 models (Table 6). These include serial correlation, normality, and heteroscedasticity tests. For this model, the null hypothesis of no serial correlation, homoscedasticity, or normality cannot be rejected. This indicates that the NARDL1 model is free of serial correlation and heteroscedasticity. According to the results of the diagnostic tests, the LM statistic is 1.248211, with a probability value of 0.3218. As a result, we accept the null hypothesis in this analysis and conclude that the model does not have serial correlation. The F-statistic for the heteroscedasticity test is 0.723784 and a probability value of 0.6383, which is >0.05 significance level, indicating that the model is homoscedastic. For NARDL1, the null hypothesis of no serial correlation,

Graph 2: CUSUM and CUSUM squares tests



Source: Authors

homoscedasticity, and normality is not rejected. The NARDL2 model stability is also explained accordingly.

4.6. Stability Tests

The CUSUM and CUSUM squares tests are used to test whether the coefficients of the estimated models remain constant over time, which is an indicator of model stability.

The results of the CUSUM and CUSUMSQ stability tests are shown in Graph 2. The plot of the tests at the 5% significance level shows that the model is stable, as the significance of not exceeding the critical thresholds is significant. This test is also used to study the long-term dynamics of the regression.

5. CONCLUSION

For Kazakhstan, where the main source of freight transport is road transport, it is important to study and evaluate the factors affecting its price. For this purpose, the research work created two NARDL models. The following variables were taken for the study: Automobile cargotunrover (mln tonna-km), Transport consumer price index, Diesel price, Total final energy consumption in thousands of tons of oil equivalent in TRANSPORT, Inflation, Lenth of internal public roads (km), Carbon dioxide (CO_2) emissions from transport (Energy) (Mt CO_2e), ICT service exports (BoP, current US$), Fixed broadband subscriptions, Individuals using the Internet (% of population).

The results of the NARDL1 model are as follows: Length of internal public roads, Carbon dioxide (CO_2) emissions from Transport (Energy) (Mt CO_2e) have a positive impact on the volume of truck traffic in both the long and short term. Individuals using the Internet (% of population), Total final energy consumption in thousands of tons of oil equivalent in TRANSPORT have a negative impact on the volume of truck traffic in both the long and short term.

The results of the NARDL2 model are as follows: Transport consumer price index, Diesel price, Inflation factor have a positive impact on road freight turnover in both the long and short run. ICT service exports (BoP, current US$), Fixed broadband subscriptions factors have a negative impact on road freight turnover in both the long and short run.

5.1. Some Policy Implications

It can be assumed that the negative impact of digitalization on the volume of truck traffic is due to the fact that a number of information that was previously transmitted through paper is now available through digital sources. The influence of other factors reflects economic laws. As Kazakhstan is a country that carries a large number of transit trucks in Central Asia, it is appropriate to reconsider environmental tax rates, since the growth of truck traffic leads to an increase in CO_2 emissions and harms the environment.

REFERENCES

Aitkaliyeva, A., Galiyeva, A., Toxanova, A. (2021), The current state of transport infrastructure in the Republic of Kazakhstan. Public Administration and Civil Service, 4(79), 85-93.

Al-Lami, A., Török, A., Alatawneh, A., Alrubaye, M. (2025), Future energy consumption and economic implications of transport policies: A scenario-based analysis for 2030 and 2050. Energies, 18(12), 3012.

Assanova, A., Jaroslaw, K. (2025), The macroeconomic effects of fiscal decentralization reforms in Kazakhstan: Evidence from regional data. Public and Municipal Finance. 14, 14-25.

Atabani, A.E., Badruddin, I.A., Mekhilef, S., Silitonga, A.S. (2011), A review on global fuel economy standards, labels and technologies in the transportation sector. Renewable and Sustainable Energy Reviews, 15(9), 4586-4610.

Ayaganova, A.Z. (2024), Transport Logistics in Kazakhstan - Problems and Development Prospects. Science and Worldview, 21. Available from: https://cyberleninka.ru/article/n/transportnaya-logistika-v-kazahstane-problemy-i-perspektivy-razvitiya [Last accessed on 2025 Nov 17].

Bodaubayeva, G., Holzhacker, H., Beifert, A., Zhaken, N. (2024), Cross-border interaction between Kazakhstan and Uzbekistan in logistics: Conceptual approaches. Economy: Strategy and Practice, 19(4), 85-103.

Chatti, W. (2021), Moving towards environmental sustainability: Information and communication technology (ICT), freight transport, and CO_2 emissions. Heliyon, 7(10), e08190.

Chevance, G., Andrieu, B., Koch, N., Tonne, C., Nieuwenhuijsen, M., Bernard, P. (2024), How gasoline prices influence the effectiveness of interventions targeting sustainable transport modes? NPJ Sustainable Mobility and Transport, 1, 17.

Dildebayeva, Z., Kakizhanova, T., Andabayeva, G., Askarova, Z., Oralbayeva, Z. (2025), Impact of oil price, CO_2 emissions and renewable energy consumption on socio-economic development: Asymmetric evidence from Kazakhstan. International Journal of Energy Economics and Policy, 15(4), 378-387.

Domagała, J., Kadłubek, M. (2023), Economic, energy and environmental efficiency of road freight transportation sector in the EU. Energies, 16(1), 461.

Eurostat. (2025), Final Energy Consumption in Transport – Detailed Statistics. Available from https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Final_energy_consumption_in_transport_-_detailed_statistics [Last accessed on 2025 Nov 24].

Franco, S. (2014), Analysis of road transport energy consumption and emissions: A case study. International Journal of Energy Sector Management, 5, 494-500.

Hasanuzzaman, M., Islam, M.A., Rahim, N.A., Yuan, Y. (2020), Energy demand. In: Hasanuzzaman, M., Rahim, N.A., editors. Energy for Sustainable Development. United States: Academic Press. p41-87.

Haxhimusa, A., Liebensteiner, M. (2025), Fuel prices as a driver of sustainable mobility: Impacts on traffic volume and vehicle choice. Energy Economics. 148, 108617.

Iamandii, A., Titu, A.M., Stan, N. (2025), Cost analysis in the field of road freight transport: A specific approach. Proceedings of the International Conference on Business Excellence, 19, 2243-2255.

IEA. (2025), Energy Efficiency Policy Toolkit 2025. Paris: IEA.

Jacyna, M., Wasiak, M. (2015), Costs of road transport depending on the type of vehicles. Combustion Engines, 162, 85-90.

Kakizhanova, T., Askarova, Z., Amirova, A., Baitanayeva, B., Andabayeva, G. (2024), Impact of oil price, CO_2 emissions, inflation and economic growth on FDI inflow: Case of Kazakhstan. International Journal of Energy Economics and Policy, 14(6), 484-491.

Kaza, N. (2020), Urban form and transportation energy consumption. Energy Policy, 136, 111049.

Khamdamov, S.J., Giyosidinov, B., Egamberdiev, O., Nosirova, N., Mamadiyarov, Z., Makhmudov, S., Ruzieva, D. (2025), The Role of Digitalization in Optimizing Freight Turnover and Enhancing Export Efficiency in Railway Networks. In: ICFNDS '24 Proceedings.

ACM. p253-260.

Köseoğlu, A.M. (2025), Energy efficiency in the road transportation sector. In: Sogut, M.Z., Koray, M., editors. Energy Rationality and Management for Decarbonization. Berlin: Springer.

Kpodar, K., Liu, B. (2022), The distributional implications of the impact of fuel price increases on inflation. Energy Economics, 108, 105909.

Li, C., Wang, F. (2025), Management and control decision of energy intensity in logistics industry under the background of dual carbon strategy in China. Scientific Reports, 15, 21732.

Link, S., Stephan, A., Speth, D., Plötz, P. (2024), Rapidly declining costs of truck batteries and fuel cells enable large-scale road freight electrification. Nature Energy, 9, 1032-1039.

Milewski, D., Milewska, B. (2023), Efficiency of the consumption of energy in the road transport of goods in the context of the energy crisis. Energies, 16(3), 1257.

Nurgaliuly, A., Smagulova, S. (2025), Economic assessment of energy security of the regions of Kazakhstan. Economics – Innovative and Economic Research Journal, 13(2), 223-243.

Ong, H.C., Mahlia, T.M.I., Masjuki, H.H. (2012), A review on energy pattern and policy for transportation sector in Malaysia. Renewable and Sustainable Energy Reviews, 16(1), 532-542.

Polukhina, E., Mizanbekova, S. (2022), Analysis of the transport and logistics complex of the Republic of Kazakhstan. Eastern-European Journal of Enterprise Technologies, 5, 21-31.

Pramuanjaroenkij, A., Kakaç, S. (2023), The fuel cell electric vehicles: The highlight review. International Journal of Hydrogen Energy, 48(25), 9401-9425.

Przekota, G., Szczepańska-Przekota, A. (2024), How road and rail transport respond to economic growth and energy prices: A study for Poland. Energies, 17(22), 5647.

Ragozin, M.S. (2024), Factors influencing the current state and efficiency of forecasting volumes of cargo transportation carried out by road transport in Russia. Natural Sciences and Humanities, 4(54), 197-203.

Rasool, Y., Zaidi, S.A.H., Zafar, M.W. (2019), Determinants of carbon emissions in Pakistan's transport sector. Environmental Science and Pollution Research, 26, 22907-22921.

Saktaganova, G., Bakirbekova, A., Zamanbekova, A. (2024), Current state of transport and logistics industry of Kazakhstan. Bulletin of Toraighyrov University: Economics Series, 4, 352-366.

Sharapiyeva, M., Kunanbayeva, D., Nurseiytova, G., Kozhamkulova, Z. (2019), Energy efficiency of transport and logistics infrastructure: The example of Kazakhstan. International Journal of Energy Economics and Policy, 9, 331-338.

Shedenov, U.K., Askarov, G.A. (2018), Methods to improve the efficiency of road freight transport. Economy: Strategy and Practice, 1, 93-99.

Sladkowski, A., Turaev, K. (2024), Regional Comparison of Public Railway for Passenger Transportation in Uzbekistan by Using the Analytical Hierarchy Method. In: 2024 3rd International Conference on Problems of Logistics, Management and Operation in the East-West Transport Corridor (PLMO). IEEE. pp. 1-5.

Smith, C.B., Parmenter, K.E. (2016), Transportation. In: Energy Management Principles. 2nd ed. Amsterdam: Elsevier. p219-227.

Song, M., Wu, N., Wu, K. (2014), Energy consumption and energy efficiency of the transportation sector in Shanghai. Sustainability, 6(2), 702-717.

Wang, Z., Gao, L., Wang, W. (2025), The impact of supply chain digitization and logistics efficiency on the competitiveness of industrial enterprises. International Review of Economics and Finance, 97, 103759.

Zheng, C., Qiu, X., Mao, J., Yu, L. (2017), Energy Consumption in Freight Logistics. In: SAEME Proceedings. p52.

Zhumanov, A.U., Kegenbekov, Z.K., Toluev, Y.I. (2024), State of logistics development and transit potential of international corridors of the Republic of Kazakhstan. Bulletin of Turan University, 4, 200-212.

Zou, G., Chau, K.W. (2019), Long- and short-run effects of fuel prices on freight transportation volumes in Shanghai. Sustainability, 11(18), 5017.