CO_2 Emissions in Lithuania's Transport Sector: Current Trends and Mitigation Approaches

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Abstract**----** This study examines the trends, challenges, and potential mitigation strategies for CO_2 emissions in Lithuania's transportation system. The analysis is based on historical emission data. It includes a regression analysis to assess the impact of key factors, including vehicle fleet composition, fuel types, traffic intensity, and urban transport patterns, on CO_2 emissions. The study identifies major challenges in decarbonizing the transport sector, including the slow adoption of electric vehicles, limited infrastructure for sustainable mobility, and economic and policy constraints. Furthermore, the research explores mitigation strategies, such as electrification of transport, promotion of public transit, optimization of freight logistics, and implementation of policy incentives for low-emission technologies. The findings provide evidence-based insights for stakeholders aiming to reduce greenhouse gas emissions and support sustainable transportation development in Lithuania.

Symbols CO_2 — carbon dioxide (greenhouse gas).

Keywords — CO_2 emissions, transportation sector, regression analysis, decarbonization, sustainable transport.

I. Introduction

Lithuania, as a member of the European Union, is committed to reducing greenhouse gas emissions under the European Green Deal and the National Energy and Climate Plan (NECP). The transport sector represents a major contributor to CO_2 emissions in Lithuania, posing a significant challenge to the nation's ability to fulfill its climate commitments. The transport sector has emerged as the primary contributor to greenhouse gas (GHG) emissions in Lithuania, accounting for nearly one-third of the nation's total emissions. The period from 2005 to 2023 witnessed a substantial escalation in transport-related emissions, with levels rising by nearly 46%. This increase is largely attributable to road transport, which accounts for more than 95% of the sector's emissions.

Over the past decade, transport emissions in Lithuania have continued to grow, driven by increasing road freight and passenger transport, increasing car ownership, and economic growth [1]. While technological solutions such as electric vehicles or advanced fuels dominate public discourse, there is increasing emphasis on the need for systemic change: promoting sustainable mobility, refocusing investments on rail, cycling, and pedestrian infrastructure, and applying smart data solutions [2], [3]. By integrating circular economy principles with digitalisation opportunities, significant efficiency and emission reduction results could be achieved in the transport sector [2].

This study aims to analyze historical emission trends, identify the principal factors influencing these emissions, and evaluate the effectiveness of current mitigation policies.

II. Review Of The Current Situation In Lithuania

The transport sector is one of the most significant sources of greenhouse gases (GHG) in Lithuania and the entire European Union. According to the European Environment Agency (2022) [2], transport emissions account for about a quarter of all EU CO_2 emissions, and in Lithuania, this proportion is even higher – transport generates more than 30% of all national emissions. In 2022, the transport sector in Lithuania consumed about 25.7 TWh of final energy, which amounted to as much as 40.4% of the country's total final energy consumption [4]. These indicators show not only the energy intensity of the transport sector, but also its high dependence on fossil fuels, especially diesel and gasoline.

The integration of circular economy principles and digital technologies is increasingly recognized as essential for enhancing transport efficiency and reducing environmental impacts. According to the European Environment Agency (2022) [2], circular economy strategies, such as managing vehicle lifecycles, increasing the reuse and recycling of transport materials, and promoting shared mobility, combined with digital tools for logistics and traffic optimization, can significantly reduce emissions and resource consumption in the transport sector. However, Lithuania faces structural challenges that impede these advancements. A primary issue is the outdated vehicle fleet: as of 2022, the Lithuanian transport sector included approximately 1.5 million passenger vehicles, 69% of which were diesel-powered, with an average age of 15 years [4], [5]. These vehicles emit between 160 and 170 grams of CO_2 per kilometer, well above the EU average, reflecting the fleet's high emission intensity and dependence on fossil fuels. The primary issue is an aging and polluting car fleet: in 2023, 77.1% of cars were more than 10 years old, and 25.9% were over 20 years old. Registration of electric cars is growing, but in 2023, they accounted for only 8.2% of all new registrations, less than the EU average (14.5%). Petrol (including hybrid) cars still dominate in Lithuania – 76.4%. Public transport use is one of the lowest in the EU: in 2022, 92.9% of trips were made by car, and only 1.1% by train (one of the lowest values in the EU). Municipal transport policies are uncoordinated, and there is a lack of intercity connections and promotion of low-emission transport [6].

Despite national climate policies promoting the adoption of electric vehicles, public transport development, alternative

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fuels, and carbon taxation, Lithuania has seen little reduction in transport sector CO_2 emissions. The slow modernization of the vehicle fleet and the sluggish adaptation of infrastructure to alternative fuels remain significant barriers to emission reduction efforts [7].

III. METHODOLOGY

The methodology of this study is based on quantitative regression analysis, the aim of which is to identify the main factors determining CO_2 emissions in the transport sector. The empirical analysis is based on annual data covering the period 2015–2024. The study employs econometric modelling to examine the main economic determinants of the analysed phenomenon. The selection of variables was based on an analysis of the scientific literature to ensure the theoretical validity of the model and the reliability of the results.

CO_2 emissions from the transport sector are widely discussed in the scientific literature as a complex phenomenon determined by economic, demographic, technological, and energy consumption factors. One of the key determinants is fuel consumption, which is directly linked to emissions generation. The International Energy Agency (2021) [8] emphasizes that emissions from the transport sector primarily stem from fuel combustion processes, making the structure of energy consumption a crucial element of the analysis. The developments in vehicle fuel efficiency have a significant impact on emission trends [9], while long-term effects of oil consumption and its scarcity on emission dynamics [10].

Demographic factors, particularly population size, also play a significant role in shaping transportation emissions. A growing population increases demand for transportation and, consequently, emission levels, particularly in urbanized areas [11]. Moreover, demographic changes remain one of the key factors driving the growth of road transport emissions [12]. The number of vehicles is often cited in the literature as one of the most important determinants of emissions, as it directly reflects the scale of the transportation system. The transport sector remains a significant challenge for climate change mitigation precisely because of the steadily growing vehicle fleet [13]. Data from the European Commission (2021) [14] confirm a steady upward trend in the number of vehicles, while this factor has a direct link to rising CO_2 emissions [12].

Technological factors, particularly vehicle age, are linked to emission intensity. Newer vehicles feature more advanced technologies and lower emissions. Fontaras et al., (2017) [15] show that, under real-world operating conditions, vehicle emissions depend significantly on their technological level and age, and the differences between laboratory and real-world emissions further highlight the importance of this factor.

Economic development, most commonly measured by GDP per capita, is also widely analyzed in the literature. Dargay et al. (2007) [16] find a strong correlation between income growth and an increase in the number of vehicles, while economic expansion is often associated with greater environmental impact [17]. However, properly implemented energy policies can curb emissions growth even in the face of economic growth [18].

Logistics intensity and freight transport volumes are widely recognized as among the most important determinants of CO_2 emissions in the transport sector, as they directly reflect the physical movement of economic activity and the load on the transport system. Logistics intensity, most commonly measured in tonne-kilometers (tkm), is a standard indicator used to assess the intensity of freight transport operations and the associated emissions. It is precisely the volume of transport activity, expressed in tkm, that is a key factor determining the level of CO_2 emissions in the transport sector, as emissions are directly proportional to the distance traveled and the freight transported [19]. The efficiency of the logistics system and the intensity of freight flows are the main factors shaping transport energy consumption and environmental impact [20].

Table 1 presents the economic justification of the variables included in the multiple regression model.

TABLE I. ECONOMIC JUSTIFICATION OF VARIABLES

Variables	**Variables descriptions**
Dependent variable	CO_2 emissions from road transport (thousand tonnes)
Independent variables	GDP per capita (euros)
	Vehicle age (year)
	Freight transport (thousand tonnes)
	Fuel consumption (thousand tonnes)
	Population (number of inhabitants)
	Logistics intensity (road, tkm)
	Number of vehicles (units)
	Freight per capita (tonnes per inhabitant). It is calculated by dividing the total goods carried by all transport modes (thousand tonnes) by the population, with results optionally expressed per 100 inhabitants for comparability.

Table 1 outlines the economic interpretation and justification of the variables incorporated in the empirical analysis. The dependent variable is CO_2 emissions from road transport (thousand tonnes). In EU countries, road transport accounts for approximately 70–75% of total CO_2 emissions generated by the transport sector, indicating that it is the dominant source of emissions and a key contributor to the sector's overall environmental impact. In this study, CO_2 emissions are analysed specifically within the road transport subsector, as it represents the largest source of transport-related emissions in Lithuania. Moreover, emissions in this subsector are directly influenced by a set of clear and measurable factors, including the number of vehicles, fuel consumption, the level of public transport use, and the average age of the vehicle fleet, among others.

The independent variables include a range of economic, demographic, and transport-related factors that directly or indirectly influence emission levels. GDP per capita reflects the level of economic development and associated transport demand, as well as potential shifts towards more sustainable mobility patterns. Vehicle age captures the technological efficiency of the fleet, as older vehicles tend to be less fuel-efficient and more polluting. Freight transport represents overall transport demand and the structure of modal choices within the logistics sector. Fuel consumption is directly linked to CO_2 emissions through the combustion of fossil fuels. Population and logistics intensity reflect overall mobility needs and transport activity within the economy. The number of vehicles and freight per capita further indicate the level of motorisation and dependence on transport services.

This comprehensive set of variables enables a more detailed understanding of the main drivers of emission changes. It also supports the robustness of the empirical models and enhances their practical relevance for designing effective climate policy measures in the transport sector.

Table 2 outlines the specification, structure, and key characteristics of the empirical models employed in the study.

TABLE II. MODELS EXPLANATION

Models	Model specification	
	Model structure	Model objective
Model 1 (M1) Core efficiency model	Fuel consumption (thousand tonnes) and Number of vehicles (units)	To evaluate the impact of fuel consumption and vehicle numbers on CO_2 emissions in road transport.
Model 2 (M2) Economic and logistics intensity model	GDP per capita (euros) and Goods carried by all modes of transport (thousand tonnes)	To assess how economic activity (GDP per capita) and Goods carried by all modes of transport affect road transport CO_2 emissions.
Model 3 (M3) Population and vehicle age Model	Population (number of inhabitants) and Age of transportation (year)	To evaluate the impact of population size and vehicle age on CO_2 emissions in road transport.
Model 4 (M4) Integrated logistics and energy model	Fuel consumption (thousand tonnes) and Logistics intensity (road, tkm)	To evaluate the impact of fuel consumption and logistics intensity on CO_2 emissions.
Model 5 (M5) Road transport emissions and economic model	Gross Domestic Product (GDP) per capita (euros), Freight per capita (% of total), and Fuel consumption (thousand tonnes)	To evaluate how economic activity (GDP per capita), transport efficiency, and fuel consumption affect CO_2 emissions from road transport.
Model 6 (M6) Integrated economic, logistics, and energy consumption model	Gross Domestic Product (GDP) per capita (euros), Fuel consumption (thousand tonnes), and Logistics intensity (road, tkm)	To evaluate how economic activity, logistics intensity, and fuel consumption jointly influence CO_2 emissions in the road transport sector.

In this study, six models were developed to analyse the factors driving CO_2 emissions in the road transport sector. Each model focuses on a different set of explanatory variables, including fuel consumption and vehicle numbers, economic activity, population size, vehicle age, and logistics intensity. This modelling approach allows for the identification of the most influential determinants of emissions and provides insights that can support the design of effective climate policy measures in the transport sector.

For the analysis, a multiple linear regression model was used, defined as follows [21]:

$$\gamma_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} + \varepsilon_i \qquad (1)$$

Here: γ_i denotes the dependent variable; $\beta_0, \beta_1, \beta_2, \ldots, \beta$ represent the regression coefficients; $x_{1i,\ldots,} x_{ki}$ are the explanatory variables; ε_i is the stochastic error term.

In regression analysis, diagnostic test indicators are statistical measures used to evaluate whether the underlying model assumptions are satisfied and whether the model is statistically valid and correctly specified (Table 3).

TABLE III. INDICATORS OF DIAGNOSTIC TESTS

Indicator	Test description	
	Test / Statistic	***Purpose***
Pearson correlation coefficient	Pearson's r	Measures the strength and direction of the linear relationship between two variables. Values range from −1 to +1; values closer to ±1 indicate a stronger linear relationship, while values near 0 indicate a weak or no linear relationship.
Coefficient of determination	R^2	Indicates the proportion of variance in the dependent variable explained by the independent variables in the model. Values closer to 1 indicate better model fit.
ANOVA	F-statistic	Tests the overall significance of the regression model by comparing the explained and unexplained variance. A higher F-value indicates that the model provides a better fit than a model with no predictors.
p-value	Statistical significance level	Indicates the probability that the observed results occurred by chance. A p-value < 0.05 typically indicates that the results are statistically significant.
Multicolinearum (Value of Variance Inflation Factor (VIF))	Variance Inflation Factor (VIF); Tolerance = 1/VIF	Multicollinearity is assessed using VIF values. If VIF > 4 (or tolerance < 0.25), multicollinearity may be present. Low VIF values indicate that independent variables are not highly correlated with each other, meaning each variable contributes unique information to the model.
Autocorrelation (Durbin – Watson (DW) test	Durbin–Watson (DW) test	The Durbin–Watson statistic ranges from 0 to 4. A value close to 2 indicates no autocorrelation in residuals. Values approaching 0 suggest positive autocorrelation, while values near 4 indicate negative autocorrelation. This test examines whether residuals at time t are correlated with residuals at time t−1.

Souces: Montgomery et al., 2012 [22]

Diagnostic tests were performed to assess whether the key regression assumptions, such as linearity and independence of explanatory variables, were met. The results confirm that the models are statistically valid and appropriate for inference and decision-making.

IV. RESULTS

The results of the regression analysis are presented below, starting with the model goodness-of-fit indicators. Table 4 summarizes the explanatory power and statistical performance of the estimated models (M1–M6), including R-squared (R^2), adjusted R-squared (Adjusted R^2), and standard error.

TABLE IV. MODEL GOODNESS-OF-FIT INDICATORS

Model	Description		
	R-squaredR^2	***Adjusted R^2***	***Standard Error***
M1	0.767	0.700	210.16
M2	0.829	0.780	179.71
M3	0.861	0.821	162.15
M4	0.855	0.814	165.20
M5	0.879	0.819	163.19
M6	0.890	0.835	155.83

This table provides an overview of six regression models used to examine the variables influencing CO_2 emissions in the transportation industry. Each model's contribution to the overall variation in emissions is displayed in the R^2 column; the higher the value, the better the model fits the data. For instance, Model 6 explains 89% of the variation and has the highest adjusted R² (0.835), which takes into account the number of independent variables. Model 6 has the lowest standard error, at 155.83, indicating the most accurate predictions. The standard error shows the average variation between observed and anticipated values. Models 5 and 6 exhibit the best fit and are regarded as the most dependable for additional analysis and decision-making, with overall model quality and accuracy increasing from Model 1 to Model 6.

TABLE V. NOVA RESULTS FOR REGRESSION MODELS

Model		Sum of squares (SS)	df	Mean Square	F	Sig.
M1	Regression	1017195.60	2	508597.80	11.52	0.006
	Residual	309166.42	7	44166.63		
	Total	1326362.02	9			
M2	Regression	110287.77	2	550143.89	17.03	0.002
	Residual	226074.25	7	32296.32		
	Total	1326362.02	9			
M3	Regression	1142291.97	2	571145.98	21.72	0.001
	Residual	184070.06	7	2695.722		
	Total	1326362.02	9			
M4	Regression	1135312.27	2	567656.13	20.79	0.001
	Residual	191079.755	7	27292.82		
	Total	1326362.02	9			
M5	Regression	1166575.32	2	388858.44	14.60	0.003
	Residual	159786.69	7	26631.12		
	Total	1326362.02	9			
M6	Regression	1180653.49	2	393551.16	16.21	0.003
	Residual	145708.54	7	24284.76		
	Total	1326362.02	9			

Table 5 shows that all six regression models are statistically significant ($p < 0.05$), indicating that the included variables jointly explain the dependent variable. Models 3 and 4 exhibit the highest F-statistics, indicating strong explanatory power, while Model 6 also demonstrates high significance, accompanied by lower residual variation. Overall, model performance improves from Model 1 to Model 6, reflecting increasing explanatory accuracy. Models 3, 4, and 6 can therefore be considered the most reliable for further analysis, with Model 6 providing the best balance between model fit and precision.

Table 6 shows the estimated regression coefficients for models M1–M6, including unstandardized coefficients, t-statistics, p-values, confidence intervals, and multicollinearity diagnostics (Tolerance and VIF). The results enable the assessment of both the direction and strength of relationships between independent variables and CO_2 emissions in road transport.

TABLE VI. REGRESSION RESULTS AND COEFFICIENT ESTIMATES

Model	Independent variables	Unstandardized coeff. (β)	T Stat (t)	P-value (Sig.)	Collinearity statistics		95.0 % Confidence Interval	
					Tolerance	*VIF*	*Lower*	*Upper*
M1	Intercept	4733.50	4.121	0.004			2017.4	7449.5
	Fuel consumption, thousand tonnes	-12.79	-1.686	0.135	0.675	1.484	-30.7	5.1
	Number of vehicles	0.001	4.651	0.002	0.675	1.484	0.001	0.002
M2	Intercept	3113.58	6.581	0.0003			1994.9	4232.2
	Gross Domestic Product (GDP) per capita, euros	0.024	1.688	0.135	0.685	1.458	-0.01	0.06
	Goods carried by all modes of transport, thousand tonnes	0.013	3.679	0.007	0.685	1.458	0.004	0.02
M3	Intercept	35622.67	7.713	0.0001			24702.2	46543.2
	Population	-0.008	-6.03	0.001	0.931	1.074	-0.012	-0.005
	The age of transportation	-285.81	-4.13	0.004	0.931	1.074	-449.1	-122.5
M4	Intercept	5545.01	6.016	0.001			3365.7	7724.3
	Fuel consumption, thousand tonnes	-9.05	-1.629	0.147	0.778	1.285	-22.2	4.08
	Logistics intensity (road), tkm	0.002	6.272	0.0004	0.778	1.285	0.012	0.03
M5	Intercept	4430.81	4.441	0.004			1989.6	6872.1
	Gross Domestic Product (GDP) per capita, euros	0.034	2.441	0.050	0.556	1.8	-0,0001	0.07
	Freight per capita, %	339.94	4.153	0.006	0.714	1.4	139.7	540.2
	Fuel consumption, thousand tonnes	-7.48	-1.315	0.236	0.714	1.4	-21.4	6.4
M6	Intercept	5854.11	6.516	0.0006			3656.0	8052.2
	Gross Domestic Product (GDP) per capita, euros	0.02	1.366	0.221	0.455	2.2	-0.02	0.06
	Logistics intensity (road), tkm	0.02	4.416	0.004	0.476	2.1	0.01	0.02
	Fuel consumption, thousand tonnes	-11.35	-2.062	0.084	0.714	1.4	-24.8	2.1

Model M1 indicates that the number of vehicles has a positive and statistically significant effect on CO_2 emissions ($\beta = 0.001$; $t = 4.651$; $p = 0.002$). This shows that emissions increase as the number of vehicles increases. Specifically, even a small increase in vehicle numbers is associated with a measurable rise in emissions, as reflected by the narrow confidence interval (0.001–0.002).

Meanwhile, fuel consumption shows a negative coefficient ($\beta = -12.79$), but it is not statistically significant ($p = 0.135$), meaning that its effect cannot be confirmed at the 5% significance level in this model.

The M2 model shows that goods carried by all modes of transport significantly increase emissions ($\beta = 0.013$; $t = 3.679$; $p = 0.007$), suggesting that higher transport intensity leads to higher environmental pollution. In contrast, GDP per capita is not statistically significant ($\beta = 0.024$; $p = 0.135$), so the level of economic development does not have a direct impact on emissions in this model.

In the M3 model, population size has a statistically significant negative effect on emissions ($\beta = -0.008$; $t = -6.03$; $p = 0.001$). It means that a one-unit increase in population is associated with a reduction in emissions, which have a higher efficiency in larger populations. The age of transportation also has a significant negative effect (β = -285.81; t =-4.13; p = 0.004), suggesting that changes in fleet structure or modernization are important determinants of emission reduction.

In the M4 model, logistics intensity in road transport is the strongest positive and statistically significant factor (β = 0.002; t = 6.272; p = 0.0004). This indicates that increases in tonne-kilometres transported are strongly associated with higher CO_2 emissions. Fuel consumption remains negative (β = -9.05) but statistically insignificant (p = 0.147), suggesting limited direct explanatory power in this specification.

In the M5 model, freight per capita has a strong and statistically significant effect on emissions (β = 339.94; t = 4.153; p = 0.006), indicating that higher transport demand per capita significantly increases emissions. GDP per capita is marginally significant (β = 0.034, p = 0.050), indicating a weak but borderline positive relationship between economic activity and emissions. Fuel consumption remains statistically insignificant (p = 0.236).

In the M6 model, logistics intensity is once again confirmed as one of the most important factors (β = 0.02; t = 4.416; p = 0.004), showing a strong positive effect on emissions. Fuel consumption has a negative and no statistically significant effect (p = 0.084). GDP per capita also remains statistically insignificant (p = 0.221), indicating weak explanatory power in the final specification.

Multicollinearity diagnostics show VIF values ranging from 1.07 to 2.2 across all models, which are well below the commonly accepted threshold of 5. This confirms that multicollinearity does not distort the regression estimates.

Table 7 presents the summary of the principal explanatory variables on CO_2 emissions across the analysed models.

TABLE 7. SUMMARY OF INDEPENDENT VARIABLE EFFECTS ON CO_2 EMISSIONS

Model	Independent Variable	Effect on CO_2 Emissions	
M1	Number of vehicles	+ Increases	significant
	Fuel consumption (thousand tonnes)	– Decreases	not significant
M2	Goods carried by all modes of transport, (thousand tonnes)	+ Increases	significant
	GDP per capita (euros)	+ Increases	not significant
M3	Population	– Decreases	significant
	Age of transportation	– Decreases	significant
M4	Logistics intensity (tkm)	+ Increases	very significant
	Fuel consumption (thousand tonnes)	– Decreases	not significant
M5	Freight per capita (%)	+ Increases	significant
	GDP per capita (euros)	+ Increases	marginally significant
	Fuel consumption (thousand tonnes)	– Decreases	not significant
M6	Logistics intensity (tkm)	+ Increases	significant
	Fuel consumption (thousand tonnes)	– Decreases	marginal significance
	GDP per capita (euros)	+ Increases	not significant

In summary, CO_2 emissions from road transport are primarily driven by transport activity indicators, with the number of vehicles, logistics intensity, and freight transport demand showing the strongest and most consistent positive effects. In contrast, economic variables such as GDP per capita and population exhibit only moderate and less stable influence, while the impact of fuel consumption remains weak or ambiguous, potentially reflecting improvements in energy efficiency. Overall, Models 5 and 6 provide the most comprehensive explanation of emission variability, as they integrate key economic, logistical, and energy-related factors.

V. CONCLUSIONS

The results of all six regression models demonstrate that CO_2 emissions in the road transport sector are predominantly driven by transport activity–related variables. The most reliable and statistically significant factors that have a major positive impact on emission levels are logistics intensity, the number of vehicles, freight per capita, and the goods carried by all modes of transport. These findings confirm that increasing transport demand and system intensity remain the central forces behind rising emissions.

In contrast, GDP per capita generally exhibits a weak and often statistically insignificant effect, suggesting that economic growth alone does not directly translate into higher emissions when controlling for transport activity. Meanwhile, population size and vehicle age tend to show a negative association with CO_2 emissions, which may reflect structural differences in transport systems, technological improvements, or behavioural patterns in more densely populated contexts.

Overall, the results underline the need for targeted policy measures focusing on optimizing freight transport, managing vehicle fleet growth, and accelerating the transition towards more energy-efficient and environmentally sustainable transport systems.

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