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THE IMPACT OF CO2 EMISSIONS FROM DIFFERENT TYPES OF TRANSPORT ON COUNTRIES' LOGISTICS EFFICIENCY: CASE OF ITF MEMBER COUNTRIES

Abstract

This study provides empirical evidence that CO_2 emissions from transport (total and by transport types) have an impact on countries' logistics efficiency, both in general (Logistics Performance Index) and in terms of its individual indicators (volumes of freight transport (total and by transport types) and total investments in transport infrastructure). The aim is to empirically demonstrate the impact of CO_2 emissions from different modes of transport on the logistics efficiency of countries, specifically using data from 60 International Transport Forum (ITF) member countries. The Granger causality analysis, based on VAR modeling for six periods evaluated by the World Bank (2007, 2010, 2012, 2014, 2016, 2018), demonstrates that in 50% of the countries, changes in CO_2 emissions from transport are the cause of the shifts in the Logistics Performance Index (increasing emissions can impede logistics efficiency). The sample was reduced to these countries for the regression modeling. Regression modeling (with fixed and random effects, Hausman test, for 2002–2021 on panel data for countries in which direct causality was confirmed) showed that a one-unit increase in total CO2 emissions from transport (in general and in air transport) is associated with 0.12 and 0.21 decrease in total investments in transport infrastructure. An increase in road CO2 emissions is associated with a 0.49 decrease in road freight transport (ton-km per thousand units of GDP). An increase in CO2 rail emissions is associated with a 0.15 increase in total investments in transport infrastructure and a 0.12 increase in total freight transport.

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INTRODUCTION

Improved countries' logistics performance can contribute to national and global goals, including emissions reduction targets. As countries strive to meet the SDGs, integrating environmental considerations into logistics performance evaluations is crucial. Logistics contributes significantly to greenhouse gas emissions, and understanding this relationship can inform policies aimed at reducing carbon footprints. Environmental impact during transportation by various modes of transport, particularly the impact of CO2 emissions from transport on sustainable logistics development, is highly relevant and timely.

Governments increasingly impose regulations to reduce transport emissions. Compliance with these recommendations can affect logistics operations and costs. Companies that adapt effectively may see improved logistics performance, while those that do not may face penalties or operational disruptions. Companies with high CO2 emissions may suffer reputational damage, leading to a loss of business. This can affect their logistics performance, as stakeholders favor companies with robust sustainability practices. In addition, higher emissions typically correlate with higher fuel consumption, increasing operational costs. This can impact a company's competitiveness and its ability to invest in logistics improvements.

Companies should be increasingly aware of the carbon footprint of their logistics activities. Those with lower emissions may have a competitive advantage in markets where sustainability is prioritized (Lima, 2024). They often invest in more efficient technologies and practices, such as electric vehicles or alternative fuels. These investments can enhance logistics performance.

The World Bank calculates the Logistics Performance Index (LPI), which covers estimates of the efficiency of customs clearance, the quality of trade and transport infrastructure and logistics services, the timeliness of delivery, and the tracking ability (Arvis et al., 2023). However, while the LPI is a valuable tool for assessing logistics efficiency and effectiveness, it may overlook critical environmental metrics. By incorporating CO2 emissions data, it will be possible to provide a more comprehensive evaluation of logistics performance that aligns with sustainability objectives.

CO2 emissions from transport can significantly affect the LPI and overall logistics potential. High CO2 emissions often indicate inefficient logistics practices, such as excessive fuel consumption, poor route optimization, or reliance on older, less efficient vehicles. These inefficiencies can lead to lower scores on the LPI, which measures aspects like timeliness, infrastructure quality, and service reliability.

Overall, CO2 emissions from transport are interconnected with logistics performance and potential. By addressing emissions through improved practices and technologies, governments and companies can enhance their logistics performance, align with sustainability goals, and potentially improve their standing in measures like the LPI.

Therefore, checking the assumption that CO_2 emissions from transport have an impact on countries' logistics efficiency, both in general and in terms of its individual indicators, is a relevant research issue.

1. LITERATURE REVIEW

The influence of CO2 emissions from transport on the sustainable development of logistics in various countries is a topical research subject. Researchers constantly emphasize the need for a comprehensive approach to evaluating the efficiency of logistics, which will necessarily consider the impact on the environment. Sustainable logistics practices are increasingly recognized as essential for long-term economic viability and environmental responsibility (Ahmad et al., 2021; Andrei et al., 2021). The focus is put on the complex relationships among natural resources, technological innovations, economic growth, and the ecological footprint, especially in emerging economies (Ahmad et al., 2020; Chygryn et al., 2023; Chygryn & Shevchenko, 2023).

This comprehensive approach emphasizes the importance of adapting to new realities and developing sustainable practices that can drive economic growth while promoting global social and ecological development and contribute to a more resilient and equitable economic future (Sineviciene et al., 2019; Andrei et al., 2023; Bhandari, 2023; Richardson, 2023). Didenko et al. (2021), Melnyk et al. (2022, 2023), and Masala (2023) put attention on the role of adaptation strategies and minimizing negative consequences of environmental changes for sustainable development and the well-being of countries.

To ensure the sustainability of logistics activities, either environmental management and risk management of foreign economic and logistics activities, which is closely related to the chosen strategy of the enterprise and ensures its sustainable development, is an equally urgent issue (Starchenko et al., 2021; Sotnyk et al., 2023; Ivanova et al., 2024). Bilan et al. (2020) analyzed how pollution influences the carbon intensity of GDP. The corresponding challenge relates to the potential for

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enhancing energy efficiency (Grebski & Kuzior, 2022), energy balance transformation (Ziabina et al., 2023), and reducing the energy intensity of the economy (Gualandri & Kuzior, 2024).

Nowadays, there are complex relationships between CO2 emissions from transport and the sustainable development of logistics (Magazzino et al., 2021; Wan et al., 2022). Thus, the importance of integrated policies, technological innovations, and strategic initiatives to reduce emissions and improve the efficiency of logistics is emphasized, as well as studying the implications and effects of different temporal orientations while promoting sustainability in the transport sector. Ferrer and Thomé (2023) also highlight a comprehensive framework for understanding the complex interrelationships among sustainability dimensions within the transportation sector. The identified trade-offs emphasize the necessity for tailored approaches that consider specific national and modal circumstances and call attention to the often-overlooked consequences and disadvantages of mitigation efforts, advocating for a more holistic examination of these factors. Ultimately, addressing these challenges is crucial for advancing sustainable transportation solutions and achieving broader climate goals.

Artyukhova et al. (2022) and Badreddine and Larbi Cherif (2024) reveal a negative relationship between renewable energy consumption and CO2 emissions, as well as domestic gas emissions, highlighting the potential of renewable energy to mitigate environmental impacts in the context of investigation of interconnections between economic, ecological, and social development scenarios in promoting sustainable energy development. In these case different practices and instruments are proposed, for example environmentally related taxes (Plysa et al., 2022), carbon taxes (Kosova et al., 2023), budgetary stimulation mechanisms (Dobrovolska et al., 2024a, 2024b, 2024c), financial policy' instruments (Krause et al., 2024), reporting and auditing (Yoshimori, 2024) in the sphere of sustainable transport and energy. A comprehensive set of the above measures is proposed to effectively implement this mechanism and achieve resource-efficient production outcomes. Overall, Kuzior et al. (2022) underscored the importance of integrating circular economy principles into strategic planning for sustainable business development.

Herold and Lee (2017) and Abareshi and Molla (2013) indicate an overall increase in carbon management practices within the logistics and transportation sectors, reflecting a growing awareness and response to environmental sustainability. In addition, they emphasize the need for better metrics and transparency in reporting carbon performance (Yadav & Yadava, 2023). With growing regulatory requirements and market pressures to reduce carbon footprints, logistics performance metrics need to align with sustainability goals (He et al., 2017). Mentel et al. (2020) revealed that economic, energy, and environmental security indicators exhibit systemic interrelationships. The evaluation demonstrates that environmental and energy security are more closely linked compared to the relationships between environmental-economic and energy-economic security. Therefore, this study proposed an integrated index encompassing environmental, energy, and economic security, which was developed and assessed, highlighting the connections between individual indicators. This integrated approach offers a comprehensive understanding of how these security dimensions interact with one another.

Including emissions in world indexes would allow countries to benchmark their performance against others in terms of both logistics efficiency and environmental impact. This could facilitate knowledge sharing and the adoption of best practices in sustainable logistics, promote more responsible logistics practices, and drive progress toward global climate goals. However, at present, the main components of the LPI announced by the World Bank, which are to be considered during the evaluation, do not properly fix the researched aspect. Therefore, the issue of economic-mathematical confirmation of existing connections and quantitative assessment of effects and consequences remains relevant and requires further research.

The aim of this study is to empirically demonstrate the impact of CO_2 emissions from different modes of transport on the logistics efficiency of countries. The study explores the relationship between CO_2 emissions and various indicators of logistics efficiency, such as the Logistics Performance Index (LPI), freight transport volumes, and infrastructure investments.

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The hypothesized assumption is that increased CO_2 emissions from transport (total and by transport type) correlate with decreased countries' logistics efficiency measured by the Logistics Performance Index, the volume of freight transport (by type) and total investments in transport infrastructure, that potentially hindering sustainable logistics development.

2. METHODS

The research sample includes data for 60 of 69 International Transport Forum member countries (intergovernmental organization at OECD) (ITF, n.d.), including Azerbaijan, for which data for all investigated indicators are available. In addition, according to the authors' beliefs, Armenia and the Russian Federation were excluded from the sample.

At the first stage of the study, Granger causality analysis (Granger, 1969) is performed based on current VAR modeling estimates for sample countries to determine whether the change in volume of CO2 emissions from transport (ITF, 2024; OECD, n.d) is the cause of the change of Logistics Performance Index. Generally, it is available for seven periods evaluated by the World Bank from 2007 to 2023, but however, taking into account the lack of available data for another indicator for 2023 at the present time, the study period covers a time series of six periods – 2007, 2010, 2012, 2014, 2016, and 2018 (World Bank, n.d.).

Overall, the Granger test is a valuable tool in time series analysis, helping to uncover predictive relationships that can inform decision-making and research. It is used primarily to determine whether changes in one variable (time series) precede and potentially cause changes in another variable. Understanding causal relationships can improve model performance. If one time series Granger-causes another, it can be used as a predictor in forecasting models, enhancing the accuracy of predictions.

Performing a Granger test based on vector autoregression (VAR) estimates involves several steps:

1) fitting the VAR Model;
2) conducting the Granger Test (Rossi & Wang, 2019; Baum et al., 2022).

H0: *The first series is not helpful in predicting the second.*

H1: *The first series helps predict the second.*

If the p-value is less than the selected significance value (for example, 0.05), then the null hypothesis is rejected. This suggests that the first series may be useful for predicting the second. If the p-value is greater, then there is no reason to reject the null hypothesis (Granger, 1969).

So, this method is chosen to formally test hypotheses about the relationships between variables, providing a statistical framework for analysis and confirmation of significant relationship that warrant further investigation.

Before conducting the Granger test, descriptive statistics and data normalization are applied. Descriptive statistics (mean, minimum, maximum, standard deviation, etc.) help to understand the central tendency, variability, and distribution of time series data for assessing the data nature. Normalizing data is important because time series data are measured in different units and have vastly different scales. Therefore, normalization can help to meet the assumptions required for the Granger test, such as normality and homoscedasticity, to ensure that the analysis is not biased toward variables with larger magnitudes and to enhance the validity and interpretability of results.

In the second stage, the sample is reduced to 30 countries in which causality is confirmed. Regression modeling for panel data for 2002–2021 (with fixed and random effects, Hausman test) of the impact of CO2 emissions from transport (total and by transport types) (ITF, 2024; OECD, n.d) on individual indicators of logistics efficiency (volumes of freight transport (total and by transport types) (ITF, 2024; OECD, n.d) and total investments in transport infrastructure) (ITF, 2024; OECD, n.d) is applied.

The choice between regression models for panel data estimation with fixed and random effects hinges on the underlying assumptions about the

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relationship between the independent variables and the unobserved individual effects. The fixed effects model assumes that individual-specific effects are correlated with the independent variables. It controls for time-invariant characteristics by focusing on within-individual variation. In turn, the random effects model assumes that individual-specific effects are uncorrelated with the independent variables. It utilizes both within and between individual variations, allowing for a more efficient estimation if the assumption holds (Arellano, 2003; Allison, 2009; Stata, n.d.).

The Hausman test is used to compare these two models and decide which model is more appropriate. The null hypothesis (*H0*) states that the random effects model is consistent and efficient. The alternative hypothesis (*Ha*) suggests that the fixed effects model is preferred due to the correlation between the individual effects and the regressors. A significant chi-squared statistic (e.g., $p < 0.05$) indicates that the fixed effects model is preferred. If the p-value is low, the null hypothesis is rejected, suggesting the presence of a correlation that makes the random effects model inconsistent (Hausman, 1978). Therefore, the Hausman test ensures that estimates are valid and reliable based on the underlying assumptions of the data.

3. RESULTS AND DISCUSSION

For data preparation before Granger test and regression modeling, descriptive statistics and normalization were applied to increase the reliability and validity of research findings and to obtain more accurate conclusions about the causal relationships between time series, that ultimately leads to better decision-making based on analysis (Table 1).

The minimum and maximum values of CO2 (21.79643 and 363.0454) provide important insights into data. Knowing the minimum and maximum can help to understand the data distribution. The difference between the maximum and minimum values indicates the range of dataset (363.0454 – 21.79643 = 341.24897). In this case, large range suggests significant variability in data.

The range of minimum and maximum values of LPI (2.081376 and 4.225967) indicates a relatively small variability (4.225967 – 2.081376 = 2.144591) in this dataset compared to the previous indicator. The proximity of the minimum and maximum values suggests that the data points are likely clustered close together. This could indicate a more consistent or homogeneous dataset.

However, this indicator is on a different scale than the previous one, so it requires applying the normalization technique to conduct further analyses and reduce the impact of the range on results. In STATA 18, the following commands were applied:

- egen minLPI = min (LPI);
- egen minCO2 = min (CO2);
- egen maxLPI = max (LPI);
- egen maxCO2 = max (CO2);
- gen nLPI = (LPI – minLPI) / (maxLPI – minLPI);
- gen nCO2 = (CO2 – minCO2) / (maxCO2 – minCO2).

Then, the data are declared as time series by the tsset command.

After that the var command is applied to fit a VAR model (var nLPI nCO2, lags (1/1)) and the Granger Test is performed using the vargranger command to conduct the Granger causality (Appendix A, Table A1).

Table 1. Summary statistics

Variable	Observation number	Mean	Std. dev.	Min	Max
LPI	360	3.291219	.5328081	2.081376	4.225967
CO2	360	97.65844	54.53624	21.79643	363.0454

Note: LPI – Logistics Performance Index score, CO2 – the value of CO2 emissions from transport in tons per one million units of current USD GDP.

Test output is checked for the *p*-value. If the *p*-value is less than the significance level (e.g., 0.05), the null hypothesis is rejected, indicating that the dependent variable causes the result variable.

H0: *The series of dependent variables is not helpful in predicting the series of result variables.*

H1: *The series of dependent variables helps predict the series of result variables.*

For Albania, the *p*-value of the Granger test is 0.05, at the limit of significance. The null hypothesis is rejected, indicating that the dependent variable (CO2) causes the result variable (LPI) and has information that can be useful for its prediction. Since the *p*-value is 0.050, this is often considered significant; however, it is borderline.

In the second line for Albania, the *p*-value of the Granger test is 0.411; this means that there is no reason to reject the null hypothesis. This indicates that the dependent variable (LPI) is not statistically significant for predicting the result variable (CO2). The value of 0.411 is well above the standard level of significance (0.05), so the probability of the observed result when the null hypothesis is correct is quite high.

In case of Argentina, the *p*-value of Granger test is 0.000; it means that the null hypothesis is rejected, indicating that dependent variable (CO2) causes the result variable (LPI) and has a statistically significant effect on its prediction. A value of 0.000 is very low and indicates that the probability of obtaining such a result under the correct null hypothesis is extremely low. This confirms the existence of a significant connection between the series.

Corresponding results were similarly obtained and interpreted for all countries of the sample (Appendix A, Table A2).

The results of the Granger causality analysis show that the change in the volume of CO2 emissions from transport is the cause of changes in the Logistics Performance Index score in 30 of the 60 sample countries (50%). This supports the notion that increasing emissions may hinder logistics performance.

An inverse causal relationship is also revealed: changes in the Logistics Performance Index score cause changes in the volume of CO2 emissions from transport in 16 countries of the sample. In these countries, improvements in LPI scores have led to changes in CO2 emissions. This may imply that better logistics performance can contribute to lower emissions, possibly through more efficient transport practices.

Bidirectional Granger causality is identified in eight countries of the studied sample, highlighting a more complex interplay where each factor influences the other.

Generally, the assumption about the impact of CO2 emissions from transport on sustainable logistics development is confirmed. These results reinforce the assumption that CO2 emissions from transport have a significant impact on sustainable logistics development. This underscores the importance of addressing emissions to enhance logistics performance and promote sustainability in the transport sector.

In the second stage of the study, the sample was reduced to 30 countries in which causality was confirmed. The period is 20 years (2002–2021). The resulting panel data consist of 600 observations. Similarly to the previous stage, the data were normalized, taking into account the different dimensions of the indicators and the significant difference between the minimum and maximum values.

Regression modeling for panel data (with fixed and random effects) of the impact of CO2 emissions from transport (total and by transport types) on individual indicators of logistics efficiency (volumes of freight transport (total and by transport types) and total investments in transport infrastructure) is applied.

Table 2 presents the results of regression modeling for panel data with fixed effects to estimate the impact of CO2 emissions from transport (total and by transport types) on total investments in transport infrastructure.

The *R*-squared values indicate a relatively low overall fit, with within-group variation at 0.0557, between-group variation at 0.0788, and over-

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Table 2. The results of the fixed-effects model to estimate the impact of CO2 emissions from transport (total and by transport types) on total investments in transport infrastructure

nI	Coefficient	Std. err.	t	P>|t|	[95% conf. interval]	
nCO2	–.1292406	.0410844	–3.15	0.002	–.2099372	–.048544
nCO2_road	.1421746	.17341	0.82	0.413	–.1984312	.4827803
nCO2_rail	.1539056	.0379333	4.06	0.000	.0793984	.2284129
nCO2_air	–.213381	.0570226	–3.74	0.000	–.3253828	–.1013792
_const	.0120983	.1623021	0.07	0.941	–.3066896	.3308862

Note: nI – normalized value of total inland transport infrastructure investment per GDP; nCO2 – normalized value of CO2 emissions from transport in tons per one million units of current USD GDP; nCO2_road – normalized value of the share of CO2 emissions from road in total CO2 emissions from transport; nCO2_rail – normalized value of the share of CO2 emissions from rail in total CO2 emissions from transport; nCO2_air – normalized value of the share of CO2 emissions from international aviation bunkers in total CO2 emissions.

all variation at 0.0692. This suggests that while the model explains some variation in nI, there are other unmeasured factors influencing it. The *F*-test shows the model is statistically significant (Prob > F = 0.0000), indicating that at least one of the independent variables significantly predicts nI.

A coefficient –0.13 of nCO2 indicates that a one-unit increase in CO2 emissions is associated with a decrease in nI, statistically significant at the 0.002 level. This supports the hypothesis that higher emissions negatively impact logistics performance. The coefficient 0.14 of nCO2_road is not statistically significant (P = 0.413), suggesting that road emissions do not have a clear effect on nI. The coefficient 0.15 of nCO2_rail is statistically significant (P = 0.000), indicating that increased rail emissions correlate with higher nI, potentially suggesting efficiency gains or other positive factors associated with rail logistics. The coefficient –0.21 of nCO2_air is significant (P = 0.000), showing that air transport emissions have a detrimental impact on nI. The constant term is not statistically significant (P = 0.941), indicating that when all independent variables are zero, the expected value of nI is not statistically different from zero.

The model indicates that approximately 66.83% of the variance in nI is due to unobserved factors (u_i), highlighting the importance of considering fixed effects related to countries.

The analysis confirms that CO2 emissions from transport modes, particularly air transport and overall emissions, significantly influence logistics performance, while the effect of road emissions appears negligible. The significant relationship with rail emissions suggests an area for further exploration, particularly in understanding how rail logistics may contribute positively to performance metrics.

Table 3 shows the results of regression modeling for panel data with random effects to estimate the impact of CO2 emissions from transport (total and by transport types) on total investments in transport infrastructure.

The results from random-effects GLS regression analysis provide a complementary perspective on

Table 3. The results of the random-effects model to estimate the impact of CO2 emissions from transport (total and by transport types) on total investments in transport infrastructure

nI	Coefficient	Std. err.	z	P > |z|	[95% conf. interval]	
nCO2	–.124128	.0397056	–3.13	0.002	–.2019496	–0.463064
nCO2_road	.1130935	.0882194	1.28	0.200	–.0598133	.2860004
nCO2_rail	.1464846	.032751	4.47	0.000	.0822938	.2106755
nCO2_air	–.2063248	.0553489	–3.73	0.000	–.3148066	–0.97843
_const	.0384549	.0846593	0.45	0.650	–.1274742	.204384

Note: nI – normalized value of total inland transport infrastructure investment per GDP; nCO2 – normalized value of CO2 emissions from transport in tons per one million units of current USD GDP; nCO2_road – normalized value of the share of CO2 emissions from road in total CO2 emissions from transport; nCO2_rail – normalized value of the share of CO2 emissions from rail in total CO2 emissions from transport; nCO2_air – normalized value of the share of CO2 emissions from international aviation bunkers in total CO2 emissions.

the relationship between CO2 emissions from different transport modes and the dependent variable nI. *R*-squared values are similar to the fixed effects model, with within-group at 0.0557, between-group at 0.0760, and overall, at 0.0678. This indicates that the model explains a limited amount of variance in nI. The Wald chi-squared test indicates that the model is statistically significant (Prob > chi2 = 0.0000), suggesting at least one of the independent variables significantly predicts nI.

Coefficient –0.12 of nCO2 suggests that a one-unit increase in overall CO2 emissions corresponds to a decrease in nI, which is statistically significant (P = 0.002). This reinforces the negative impact of CO2 emissions on logistics performance. The coefficient 0.11 of nCO2_road is not statistically significant (P = 0.200), indicating that road emissions do not have a clear or significant relationship with nI. The coefficient 0.15 of nCO2_rail is statistically significant (P = 0.000), indicating that increased emissions from rail transport are positively associated with nI. This suggests that higher rail emissions might correlate with better logistics performance, possibly due to efficiency or other positive factors. The coefficient –0.21 of nCO2_air is also significant (P = 0.000), indicating that air transport emissions negatively affect nI, similar to the fixed effects results. The constant term is not significant (P = 0.650), suggesting that when all independent variables are zero, the expected value of nI does not significantly differ from zero.

The fraction of variance due to unobserved factors (rho) is approximately 68.58%, indicating that a significant portion of the variance in nI is attributable to differences between countries.

The random-effects model corroborates the findings from the fixed-effects analysis, particularly the significant negative impact of overall and air transport emissions on logistics performance. The positive relationship with rail emissions also remains significant. The limited explanatory power of both models suggests that other factors influencing nI should be considered in future analyses. Overall, these findings highlight the critical relationship between transport emissions and logistics performance, underscoring the importance of sustainable practices in the transport sector.

Hausman test compares fixed effects (b) and random effects (B) models. The output from a Hausman test (chi2(4) = $(b - B)'[(V\_b - V\_B)^{(-1)]}{}^{(b-B)}$ = 1.02, Prob > chi2 = 0.9073) means the following: coefficient nCO2 in case of fixed effect model is –0.129, while the random effect is –0.124. The difference is small (–0.005) and not statistically significant (p = 0.9073). The fixed effect of nCO2_road is 0.142 vs. the random effect of 0.113. The difference is 0.029, but again not significant. In the case of nCO2_rail, it is a similar pattern with a negligible difference. For nCO2_air, the fixed effect (–0.213) vs. the random effect (–0.206) shows a difference of -0.007, and it is not significant.

Chi-squared statistic (chi2(4) = 1.02) tests the null hypothesis that the difference in coefficients is not systematic. Prob > chi2 = 0.9073 shows a high p-value that indicates failure to reject the null hypothesis. This suggests that the fixed effects and random effects models yield similar results, implying that the random effects model could be appropriate.

The next modeling stage is estimating the impact of CO2 emissions from transport (total and by transport types) on total inland freight transport (Table 4).

As for the fixed-effects model, the *R*-squared values indicate a strong fit for the within-group variation at 0.5016, suggesting that approximately 50% of the variation in nFT can be explained by the independent variables when looking at changes within each country. The between-group *R*-squared is 0.2570, and the overall *R*-squared is 0.2739, indicating that the model captures some variation between countries but is less effective in explaining overall differences. The *F*-statistic is highly significant (F(4, 566) = 142.43; Prob > F = 0.0000), confirming that at least one of the independent variables significantly influences nFT.

The coefficient of 0.4195 (nCO2) is highly significant (P = 0.000), indicating that a one-unit increase in overall CO2 emissions is associated with a 0.4195 increase in nFT. This suggests that higher emissions may correlate with increased freight transport, possibly due to greater demand or reliance on transport modes contributing to emissions. The coefficient of –0.0503 (nCO2_road) is

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Table 4. The results of the fixed and random-effect models to estimate the impact of CO2 emissions from transport (total and by transport types) on total inland freight transport

Fixed-effect model						
nFT	**Coefficient**	**Std. err.**	**t**	**P > |t|**	**[95% conf. interval]**	
nCO2	.4194847	.0258739	16.21	0.000	.3686641	.4703053
nCO2_road	–.0503312	.109209	–0.46	0.645	–.2648356	.1641733
nCO2_rail	.1207517	.0238894	5.05	0.000	.073829	.1676744
nCO2_air	–.0040346	.0359113	–0.11	0.911	–.0745703	0665012
_const	.0755972	.1022135	0.74	0.460	–.125167	.2763613
Random-effects model						
nFT	**Coefficient**	**Std. err.**	**z**	**P > |z|**	**[95% conf. interval]**	
nCO2	.4145313	.0259096	16.00	0.000	.3637493	.4653132
nCO2_road	.0276741	.0798639	0.35	0.729	–.1288563	.1842046
nCO2_rail	.1437181	.0223765	6.42	0.000	.0998608	.1875753
nCO2_air	–.0099364	.0361355	–0.27	0.783	–.0807608	.0608879
_const	.0024423	.0774442	0.03	0.975	–.1493455	.1542302

Note: nFT – normalized value of total inland freight transport in ton-km per one thousand units of current USD GDP.; nCO2 – normalized value of CO2 emissions from transport in tons per one million units of current USD GDP; nCO2_road – normalized value of the share of CO2 emissions from road in total CO2 emissions from transport; nCO2_rail – normalized value of the share of CO2 emissions from rail in total CO2 emissions from transport; nCO2_air – normalized value of the share of CO2 emissions from international aviation bunkers in total CO2 emissions.

not statistically significant (P = 0.645), indicating that road transport emissions do not have a clear impact on nFT. The coefficient of 0.1208 (nCO2_rail) is significant (P = 0.000), suggesting that increased emissions from rail transport positively correlate with nFT. This may indicate that rail transport is becoming a more important mode for freight as emissions increase. The coefficient of –0.0040 (nCO2_air) is also not significant (P = 0.911), suggesting that air transport emissions have little to no impact on nFT. The constant term is not significant (P = 0.460), indicating that the expected value of nFT does not significantly differ from zero when all independent variables are zero.

The fraction of variance due to unobserved factors (rho) is quite high at 92.11%, indicating that a significant portion of the variation in nFT is attributable to differences between countries.

The fixed-effects model shows that overall CO2 emissions and rail transport emissions significantly influence nFT, indicating a potential link between emissions and freight transport activity. However, road and air emissions do not appear to significantly impact nFT in this analysis. The strong within-group explanatory power suggests that variations in emissions and logistics performance are closely related, emphasizing the need for policies aimed at reducing emissions in the freight sector to promote sustainable transport practices. Further research could explore the underlying reasons for these relationships and consider other factors affecting nFT.

The results from random-effects GLS regression show within-group R-squared of 0.50080; it indicates that approximately 50% of the variation in nFT is explained by the independent variables when considering changes within each country. Between-group R-squared of 0.3338 suggests that about 33% of the variation between different groups (countries) is explained by the model. Overall R-squared of 0.3280 indicates a moderate explanatory power for the model across all observations. The Wald chi-squared test is significant (Wald chi2(4) = 567.75, Prob > chi2 = 0.0000), confirming that at least one of the independent variables significantly influences nFT.

The coefficient of 0.4145 (nCO2) is significant (P = 0.000), indicating that a one-unit increase in overall CO2 emissions corresponds to a 0.4145 increase in nFT. This suggests a positive relationship, where higher emissions may be associated with increased freight transport activity. For nCO2_road, the coefficient is 0.0277, and it is not statistically significant (P = 0.729), indicating that road transport emissions do not have a meaningful impact on nFT. The coefficient of 0.1437 for nCO2_rail is significant (P = 0.000), suggesting that increased emissions from rail transport positively correlate with nFT. This indicates that higher rail emissions may be linked to increased freight transport activity. The coefficient of –0.0099 (nCO2_air) is not significant ($P = 0.783$), suggesting that air transport emissions have little to no impact on nFT. The constant term is not statistically significant ($P = 0.975$), indicating that when all independent variables are zero, the expected value of nFT does not significantly differ from zero.

The fraction of variance due to unobserved factors (rho) is approximately 87.24%, indicating that a substantial portion of the variance in nFT is attributable to differences between countries.

Therefore, the random-effects model corroborates the findings from the fixed-effects analysis, particularly the significant positive relationship between overall CO2 emissions and freight transport. The significant effect of rail emissions on nFT suggests that rail transport plays a crucial role in freight activity, while road and air emissions do not exhibit a significant impact. This analysis underscores the importance of considering emissions in the context of freight transport and highlights the need for sustainable practices, especially in rail logistics. Future research could delve deeper into the underlying factors driving these relationships and explore additional variables that may affect nFT.

Hausman test results ($chi2(4) = (b - B)'[(V\_b - V\_B)^{(-1)}](b - B) = 21.88$, Prob > chi2 = 0.0002) indicate strong evidence against the null hypothesis. This suggests that the differences in coefficients between the fixed and random effects models are systematic rather than random. Since the fixed effects model provides consistent estimates even when the assumptions of the random effects model are violated (particularly the assumption of no correlation between the unobserved effects and the independent variables), the fixed effects model, in this case, is preferable.

In order to assess the impact of CO2 emissions by a specific mode of transport on the volume of freight transportation by the same mode of transport, separate regression models were built according to a similar algorithm – with fixed effects and with random effects, after which the optimal modification of the model was selected using the Hausman test. The summarized results are shown in Table 5.

For road transport, the Hausman test (Prob > chi2 = 0.0313) means that the null hypothesis is rejected, and the differences in coefficients are systematic. The fixed effects model is chosen. For rail transport, the Hausman test (Prob > chi2 = 0.0095) grounds that using the fixed effects model will yield more consistent and reliable estimates, too. Moreover, for air transport (Prob > chi2 = 0.0160), the result is similar – it is also necessary

Table 5. The results of regression modeling to assess the impact of CO2 emissions by a specific mode of transport on the volume of freight transportation by the same mode of transport

nFT_road	Coefficient	Std. err.	t / z	P>|t| / P>|z|	[95% conf. interval]	
Fixed-effect model						
nCO2_road	–.4941474	.1376968	–3.59	0.000	–.7646034	–.2236914
Random-effects model						
nCO2_road	–.3161608	.1106569	–2.86	0.004	–.5330443	–.0992773
Fixed-effect model						
nCO2_rail	.5028647	.0275195	18.27	0.000	.4488126	.5569169
Random-effects model						
nCO2_rail	5178298	.027044	19.15	0.000	.4648246	.5708351
Fixed-effect model						
nCO2_air	–.0221764	.0264844	–0.84	0.403	–.0741955	.0298427
Random-effects model						
nCO2_air	–.0155046	.0264467	–0.59	0.558	–.0673392	.03633

Note: nFT_road – normalized value of road freight transport in ton-km per one thousand units of current USD GDP; nFT_rail – normalized value of rail freight transport in ton-km per one thousand units of current USD GDP; nFT_air – normalized value of air freight transport in tonne-km per one thousand units of current USD GDP; nCO2_road – normalized value of the share of CO2 emissions from road in total CO2 emissions from transport; nCO2_rail – normalized value of the share of CO2 emissions from rail in total CO2 emissions from transport; nCO2_air – normalized value of the share of CO2 emissions from international aviation bunkers in total CO2 emissions.

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to choose the fixed effects model, but in this case, the obtained regression coefficient is not statistically significant.

So, the regression analysis assesses how CO2 emissions from specific transport modes (road, rail, air) impact the volume of freight transportation using the same modes. For road freight transport, the coefficient is –0.4941 (highly significant, $P = 0.000$). A one-unit increase in the share of CO2 emissions from road transport is associated with a decrease of approximately 0.4941 in the volume of road freight transport (in ton-km per thousand units of GDP). This suggests that higher CO2 emissions negatively impact road freight efficiency or demand. For rail freight transport, the coefficient is 0.5029 (highly significant, $P = 0.000$). A one-unit increase in CO2 emissions from rail is associated with an increase of 0.5029 in rail freight transport. This positive relationship suggests that higher emissions may be linked to increased rail freight activity, possibly due to greater operational demands or expansion of services.

The analysis highlights distinct relationships between CO2 emissions and freight transport volumes across different modes. Higher CO2 emissions are negatively associated with the volume of road freight transport, indicating that increased emissions may lead to reduced efficiency or demand. In contrast, higher CO2 emissions from rail transport are positively associated with increased freight transport, suggesting potential growth in rail activities as emissions rise. And there is no significant relationship between CO2 emissions and air freight transport volume, indicating that other factors may be more influential in determining air freight activity.

Some studies have also provided empirical evidence linking CO2 emissions with logistics performance indicators (or propositions to create their own complex indexes), demonstrating that reducing emissions can lead to better overall logistics outcomes (Mariano et al., 2017). The study evaluated the effectiveness of the relationship between the performance of transport logistics, which is measured using the LPI, and the total CO2 emissions in the transport sector (not taking into account the peculiarities of individual modes of transport).

Santosa et al. (2022) investigated the relationship between logistics performance and environmental performance, specifically carbon emissions, in ASEAN countries. Based on panel data from 2007 to 2018 across 10 ASEAN nations, they concluded that there is a negative and significant correlation between LPI and carbon emissions, indicating that improved logistics performance is associated with lower carbon emissions.

Karaduman et al. (2020) conducted an empirical investigation of the relationship between logistics performance and carbon emissions, but only targeting Balkan countries (11 countries). Besides, this study focuses only on one of the possible directions of investigated relationships – the impact of logistics performance on CO2 emissions (the same direction was studied by Hind and Mustapha (2022). The results indicate a positive and significant relationship between logistics performance and CO2 emissions, which demonstrates another approach and outcomes other than those in this paper.

Overall, the obtained findings underscore the need for targeted policy measures to manage emissions, especially in road transport, while recognizing the unique dynamics of rail transport that may warrant further investigation into how emissions relate to increased freight activity.

CONCLUSION

The aim of the paper is to empirically demonstrate the impact of CO_2 emissions from different modes of transport on the logistics efficiency of countries, specifically using data from 60 International Transport Forum (ITF) member countries.

Overall, the assumption that CO2 emissions from transport affect sustainable logistics development is confirmed, emphasizing the need to address emissions to improve logistics performance and promote sustainability in the transport sector. In 50% of the sample, increased CO2 emissions correlate with declines in the LPI, suggesting that higher emissions can hinder logistics effectiveness. A one-unit increase in total CO2 emissions from transport is associated with a 0.12 decrease in total investments in transport infrastructure. Air transport emissions also have a negative effect (0.21 decrease). This supports the suggestion that higher overall emissions negatively affect logistics performance.

A one-unit increase in road CO2 emissions is associated with a decrease of approximately 0.49 in the volume of road freight transport. This suggests that higher emissions may negatively impact road freight efficiency or demand. A one-unit increase in CO2 rail emissions is associated with a 0.15 increase in total investments in transport infrastructure and a 0.12 increase in total freight transport. This suggests that increased rail emissions might correlate with better logistics performance, possibly due to operational efficiencies or other positive factors. This may imply that rail transport is becoming increasingly important for freight as emissions rise.

The findings underscore the need to manage emissions for targeted policy measures for sustainable practices across transport to improve logistics outcomes. The study also emphasizes the importance of considering the specific effects of emissions on different modes of freight transport when developing sustainable transport policies. The received quantitative impact assessments can be useful for stakeholders in the field of sustainable logistics development in Azerbaijan and other ITF member countries in the context of policy improvement and related measures.

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APPENDIX A

Table A1. Granger causality test results

Country	Cause variable	Result variable	Test result	Country	Cause variable	Result variable	Test result
Albania	nCO2	nLPI	0.050	Japan	nCO2	nLPI	0.448
	nLPI	nCO2	0.411		nLPI	nCO2	0.271
Argentina	nCO2	nLPI	0.000	Kazakhstan	nCO2	nLPI	0.033
	nLPI	nCO2	0.000		nLPI	nCO2	0.811
Australia	nCO2	nLPI	0.135	Korea	nCO2	nLPI	0.469
	nLPI	nCO2	0.709		nLPI	nCO2	0.000
Austria	nCO2	nLPI	0.405	Latvia	nCO2	nLPI	0.006
	nLPI	nCO2	0.564		nLPI	nCO2	0.943
Azerbaijan	nCO2	nLPI	0.424	Lithuania	nCO2	nLPI	0.045
	nLPI	nCO2	0.796		nLPI	nCO2	0.712
Belgium	nCO2	nLPI	0.000	Luxembourg	nCO2	nLPI	0.010
	nLPI	nCO2	0.301		nLPI	nCO2	0.758
Bosnia and Herzegovina	nCO2	nLPI	0.021	Malta	nCO2	nLPI	0.859
	nLPI	nCO2	0.000		nLPI	nCO2	0.039
Brazil	nCO2	nLPI	0.286	Mexico	nCO2	nLPI	0.001
	nLPI	nCO2	0.663		nLPI	nCO2	0.151
Bulgaria	nCO2	nLPI	0.327	Moldova	nCO2	nLPI	0.051
	nLPI	nCO2	0.973		nLPI	nCO2	0.938
Cambodia	nCO2	nLPI	0.616	Mongolia	nCO2	nLPI	0.470
	nLPI	nCO2	0.000		nLPI	nCO2	0.269
Canada	nCO2	nLPI	0.296	Montenegro	nCO2	nLPI	0.002
	nLPI	nCO2	0.247		nLPI	nCO2	0.092
Chile	nCO2	nLPI	0.101	The Netherlands	nCO2	nLPI	0.004
	nLPI	nCO2	0.000		nLPI	nCO2	0.759
China	nCO2	nLPI	0.231	New Zealand	nCO2	nLPI	0.051
	nLPI	nCO2	0.000		nLPI	nCO2	0.053
Colombia	nCO2	nLPI	0.049	The North Macedonia	nCO2	nLPI	0.328
	nLPI	nCO2	0.100		nLPI	nCO2	0.346
Costa Rica	nCO2	nLPI	0.001	Norway	nCO2	nLPI	0.104
	nLPI	nCO2	0.046		nLPI	nCO2	0.376
Croatia	nCO2	nLPI	0.493	Poland	nCO2	nLPI	0.007
	nLPI	nCO2	0.623		nLPI	nCO2	0.872
The Czech Republic	nCO2	nLPI	0.473	Portugal	nCO2	nLPI	0.546
	nLPI	nCO2	0.926		nLPI	nCO2	0.514
Denmark	nCO2	nLPI	0.240	Romania	nCO2	nLPI	0.000
	nLPI	nCO2	0.074		nLPI	nCO2	0.484
Estonia	nCO2	nLPI	0.000	Serbia	nCO2	nLPI	0.850
	nLPI	nCO2	0.788		nLPI	nCO2	0.861
Finland	nCO2	nLPI	0.050	The Slovak Republic	nCO2	nLPI	0.000
	nLPI	nCO2	0.000		nLPI	nCO2	0.649
France	nCO2	nLPI	0.002	Slovenia	nCO2	nLPI	0.049
	nLPI	nCO2	0.987		nLPI	nCO2	0.708
Georgia	nCO2	nLPI	0.516	Spain	nCO2	nLPI	0.000
	nLPI	nCO2	0.036		nLPI	nCO2	0.705
Germany	nCO2	nLPI	0.048	Sweden	nCO2	nLPI	0.143
	nLPI	nCO2	0.044		nLPI	nCO2	0.520
Greece	nCO2	nLPI	0.820	Switzerland	nCO2	nLPI	0.794
	nLPI	nCO2	0.132		nLPI	nCO2	0.080
Hungary	nCO2	nLPI	0.135	Tunisia	nCO2	nLPI	0.599
	nLPI	nCO2	0.131		nLPI	nCO2	0.000
Iceland	nCO2	nLPI	0.000	Turkey	nCO2	nLPI	0.000
	nLPI	nCO2	0.001		nLPI	nCO2	0.001

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Table A1 (cont.). Granger causality test results

Country	Cause variable	Result variable	Test result	Country	Cause variable	Result variable	Test result
India	nCO2	nLPI	0.188	Ukraine	nCO2	nLPI	0.079
	nLPI	nCO2	0.000		nLPI	nCO2	0.138
Ireland	nCO2	nLPI	0.303	The United Arab Emirates	nCO2	nLPI	0.564
	nLPI	nCO2	0.952		nLPI	nCO2	0.883
Israel	nCO2	nLPI	0.001	The United Kingdom	nCO2	nLPI	0.000
	nLPI	nCO2	0.125		nLPI	nCO2	0.153
Italy	nCO2	nLPI	0.331	The United States	nCO2	nLPI	0.000
	nLPI	nCO2	0.361		nLPI	nCO2	0.628

Note: nLPI – normalized value of Logistics Performance Index score, nCO2 – normalized value of CO2 emissions from transport in tons per one million units of current USD GDP.

Table A2. The results of the determination of causality direction based on the Granger test interpretation

Country	CO2 to LPI	LPI to CO2	Bidirectional causality	Country	CO2 to LPI	LPI to CO2	Bidirectional causality
Albania	+	–	–	Japan	–	–	–
Argentina	+	+	+	Kazakhstan	+	–	–
Australia	–	–	–	Korea	–	+	–
Austria	–	–	–	Latvia	+	–	–
Azerbaijan	–	–	–	Lithuania	+	–	–
Belgium	+	–	–	Luxembourg	+	–	–
Bosnia and Herzegovina	+	+	+	Malta	–	+	–
Brazil	–	–	–	Mexico	+	–	–
Bulgaria	–	–	–	Moldova	+	–	–
Cambodia	–	+	–	Mongolia	–	–	–
Canada	–	–	–	Montenegro	+	–	–
Chile	–	+	–	The Netherlands	+	–	–
China	–	+	–	New Zealand	+	+	+
Colombia	+	–	–	The North Macedonia	–	–	–
Costa Rica	+	+	+	Norway	–	–	–
Croatia	–	–	–	Poland	+	–	–
The Czech Republic	–	–	–	Portugal	+	–	–
Denmark	–	–	–	Romania	+	–	–
Estonia	+	–	–	Serbia	–	–	–
Finland	+	+	+	The Slovak Republic	+	–	–
France	+	–	–	Slovenia	+	–	–
Georgia	–	+	–	Spain	+	–	–
Germany	+	+	+	Sweden	–	–	–
Greece	–	–	–	Switzerland	–	–	–
Hungary	–	–	–	Tunisia	–	+	–
Iceland	+	+	+	Turkey	+	+	+
India	–	+	–	Ukraine	–	–	–
Ireland	–	–	–	The United Arab Emirates	–	–	–
Israel	+	–	–	The United Kingdom	+	–	–
Italy	–	–	–	The United States	+	–	–

Note: LPI – Logistics Performance Index score, CO2 – the value of CO2 emissions from transport in tons per one million units of current USD GDP; '+' means confirmed causality, '–' means unconfirmed causality.