

## **Trade Flows and Carbon Emissions: How Far Are We from the Climate Targets?**

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# Trade Flows and Carbon Emissions: How Far Are We from the Climate Targets?

Policymakers are increasingly calling for tangible actions to meet the United Nations targets for reducing emissions to 1990s levels. This study assesses whether climate targets are attainable by 2030 for a selected set of countries, with a particular focus on the transportation sector. PyCaret's Python library is used to train and compare a range of time series models and derive transport emission forecasts of countries up to 2030. We employ a range of machine learning models, including ARIMA, AdaBoost, and Theta forecaster, using historical transport emissions data to forecast CO<sub>2</sub> emissions and assess the likelihood of countries achieving the EU Green Deal's decarbonization objectives. To further support policy design, we analyze freight modal emissions using trade flow data and group countries using the K-Means clustering based on their emission profiles. Our findings show that only two countries—Greece and Italy—are currently on track to meet the 2030 targets. The remaining nations require urgent and targeted policy reform, particularly in shifting freight transport toward lower-emission modes. We conclude by offering realistic, data-driven mitigation strategies for those unlikely to meet their commitments.

Keywords: Trade Flow; Machine Learning; Carbon Emissions; Freight Transport

## Introduction

In recent decades, climate change has emerged as a significant global challenge, driven increasingly by anthropogenic activities. Historically, climate variability has been primarily influenced by natural factors, such as volcanic eruptions and fluctuations in solar radiation (Crowley, 2000). However, industrialization, urbanization, and rapid growth in transportation have significantly increased greenhouse gas (GHG) emissions, intensifying the pace and impact of global warming. According to the latest estimates from the International Energy Agency and IPCC reports, the transport sector accounts for around one-quarter ( $\approx 24\%$ ) of global energy-related CO<sub>2</sub> emissions, with road transport remaining the dominant contributor (IEA, 2025; IPCC, 2023). Within this domain, freight transport—dominated by road and maritime modes—has seen a particularly sharp growth due to the globalization of trade and supply chains.

Recognizing the urgent need for climate action, international frameworks such as the Kyoto Protocol, the Paris Agreement, and, more recently, the European Green Deal have set ambitious decarbonization targets. The European Green Deal, for instance, aims to make Europe the first climate-neutral continent by 2050, with an interim target of reducing transport-related emissions by 90% and achieving 50% of 1990s' emissions by 2030 (European Commission, 2019). These goals underscore the central role of the transport sector in national climate agendas. Road freight—currently handling over 75% of EU inland transport—has come under intense scrutiny due to its high emissions intensity. Shifting freight to lower-emission modes, such as rail and inland waterways, is widely promoted as a strategy for achieving climate goals (European Commission, 2019).

Despite strong policy frameworks, critical knowledge gaps remain. Many existing studies analyze transport emissions either at a national level or focus on individual transport modes, often neglecting the complexity of cross-national comparisons, multimodal freight behavior, and predictive uncertainty. Moreover, few studies incorporate scenario-based forecasts to evaluate the achievability of emission targets by 2030 using advanced statistical learning approaches.

This paper makes three key contributions:

- (1) It employs a suite of machine learning models, including ARIMA, AdaBoost, and Theta Forecaster, to project CO<sub>2</sub> emissions from the transport sector across 23 countries.
- (2) It integrates freight modal split data to estimate emissions from five major modes (road, rail, maritime, inland waterways, and air); and
- (3) It utilizes K-Means clustering to categorize countries based on their projected modal emissions per capita, facilitating customized policy recommendations.

The novelty of our approach lies in its multidimensional, cross-country comparison, which links trade flows, transport structure, and emission forecasting to policy analysis. By forecasting emissions under current policy trajectories and comparing them with the EU's climate targets, we identify which countries are likely to meet their targets and which will require strategic redirection. Notably, our results reveal that only two countries—Italy and Greece—are currently on track to meet the 2030 emissions target, highlighting the gap between ambition and implementation.

To guide policy action, we further analyze the projected distribution of freight emissions by transport mode for each country. This breakdown reveals structural differences in modal dependencies, allowing us to cluster countries into “road and maritime” and “road and rail” dominated emission profiles. Such segmentation helps tailor policy interventions, such as encouraging modal shifts in the most emission-intensive freight corridors.

The paper proceeds as follows: the next section reviews the relevant literature on transport emissions, decarbonization strategies, and modal shift policies. We then describe our data sources and methodology, including the forecasting techniques and clustering procedures used. The results section presents emission forecasts, country comparisons, and clustering outcomes. Finally, we conclude by discussing the implications for transport policy and future research directions.

## **Literature Review**

### ***Emissions Forecasting in the Transport Sector***

Forecasting carbon dioxide (CO<sub>2</sub>) emissions is a crucial tool for policymakers aiming to meet climate goals, particularly in the transport sector, which remains one of the most significant contributors to global greenhouse gas emissions. A wide range of methods has been developed to predict national and sector-specific CO<sub>2</sub> emissions, each with varying levels of complexity,

data requirements, and predictive power. Existing literature includes survey-based assessments (Piecyk & McKinnon, 2013), decomposition techniques to isolate the factors contributing to emissions (Qu, 2020), and machine learning models trained on secondary data (Wen & Yuan, 2020; Ma et al., 2021; Sun et al., 2019; Zhao & Niu, 2017). While these approaches are valuable, their performance is heavily influenced by the availability and quality of historical data. Models such as regularized extreme learning machines (Sun & Sun, 2017) or kernel prediction algorithms require dense, representative data; otherwise, they risk producing skewed or inaccurate forecasts.

Existing studies provide valuable insights into transport-related emissions by focusing on specific countries, transport modes, or passenger systems (e.g., Lam et al., 2018; Kazancoglu et al., 2021; Li et al., 2021). Building on this foundation, the present study extends the literature by adopting a cross-country, multimodal freight perspective, integrating emission forecasting with a modal structure spanning five freight transport modes: road, rail, maritime, inland waterways, and air. The study also provides a policy feasibility analysis, prioritizes prediction intervals to capture uncertainty around meeting targets, and provides a scenario-based understanding of each country's trajectory toward meeting EU emission targets. This allows policymakers to evaluate not only expected outcomes but also the risks of noncompliance, enabling them to formulate proactive strategies to mitigate these risks.

Our research addresses this gap by adopting a multimodal, multi-country forecasting framework, where we explicitly incorporate prediction intervals, freight modal decomposition, and cross-country comparison to assess not only expected emission trajectories but also the feasibility and uncertainty associated with meeting EU Green Deal targets.

### ***Modal Shift and Decarbonization Strategies in Freight Transport***

Freight transport is particularly challenging to decarbonize due to its dependence on fossil fuels, entrenched infrastructure, and the complexity of global supply chains. Modal shift, the

reallocation of freight from carbon-intensive road transport to more sustainable rail or inland waterway systems, is often proposed as a key solution to reducing carbon emissions. However, the literature reveals limited and often inconclusive evidence of its effectiveness.

Chen et al. (2020) compare energy consumption and emissions between road and rail freight under various scenarios and conclude that while modal shift can reduce emissions, the associated costs may, in some contexts, outweigh environmental gains. They argue for region-specific analysis rather than a one-size-fits-all policy. This view is echoed by Pinchasik et al. (2020), who examine freight transport in Nordic countries. Their findings show that although longer trains and cross-border policies have some benefits, their standalone effects on emissions are marginal unless aligned with broader sustainability frameworks.

Zagożdżon (2023) reinforces this by identifying rail as the most sustainable mode of transport in Poland, suggesting that a modal shift is crucial but contingent upon supportive national policies. Wong et al. (2024) expand this conversation by highlighting how geopolitical events such as the Belt and Road Initiative and the COVID-19 pandemic have altered global freight patterns. Their study shows that while railway freight reduces emissions compared to road transport, its increased use has paradoxically raised emissions in urban areas along new routes, underscoring the need for targeted mitigation strategies.

Yin et al. (2024) provide a more comprehensive econometric analysis, employing an autoregressive distributed lag-error correction model, to investigate the Yangtze River Delta. They show that freight structure adjustments, particularly increasing the share of rail relative to highways, significantly suppress emissions over time. However, they also emphasize the importance of reducing energy intensity through technological upgrades and investments in infrastructure.

Jonkeren et al. (2019) present another important insight, demonstrating that the feasibility and environmental benefits of modal shifts depend on factors such as cargo type and

distance. Their findings suggest that modal shift is more effective for regional and national freight movements rather than local deliveries. Despite these insights, many studies remain case-specific, and few offer transferable policy frameworks. There is a need for broader, cross-national studies that quantify both the environmental and economic impacts of modal shift.

While the literature acknowledges the importance of modal shift as a decarbonization strategy, existing research remains fragmented. Many studies are region-specific, focus on a single transport mode, or rely on scenario analyses that do not link projected emissions to formal policy targets. Moreover, few studies combine forecasting uncertainty, modal emission structure, and cross-country comparison within a unified analytical framework. This study addresses these gaps by integrating machine learning-based emission forecasts with freight modal decomposition and clustering analysis, thereby assessing not only future emissions but also the feasibility of meeting EU Green Deal targets across countries. Therefore, our research builds on this foundation by conducting a cross-country comparative analysis, identifying not only where modal shift policies have been successful but also the reasons behind their success. We emphasize the need to integrate modal shift with electrification strategies, renewable energy transitions, and intelligent logistics systems. By doing so, we aim to offer a more holistic understanding of the potential and limitations of modal shift as a decarbonization strategy.

### ***Transport Policy and Technological Responses to Climate Change***

The literature on policy responses to transport emissions spans fiscal tools, technological interventions, and long-term strategic planning. A common theme is the need for bundled policies that act synergistically rather than in isolation.

Pal et al. (2023) propose a framework grounded in ecological modernization theory that identifies key drivers of emissions, including urbanization and population growth. Using structural modeling, they rank CO<sub>2</sub> emissions, global warming, and ozone depletion as top

concerns. However, their reliance on arbitrary weighting methods and limited expert samples undermines the robustness of their conclusions.

Ülengin et al. (2018) integrate expert judgment and scenario analysis to evaluate the effects of different policy combinations. Their study, which incorporates both global IEA scenarios and localized Turkish policies, concludes that improvements in vehicle efficiency alone are insufficient to achieve the desired results. Instead, R&D subsidies, carbon taxes, and standards for alternative fuels should be implemented in conjunction with one another. However, their work stops short of using decision-support tools that could guide policymakers in selecting optimal strategies.

Liobikienė and Miceikienė (2023) further support the role of carbon taxes and environmental regulations, finding that such instruments effectively lower emissions across transport modes. However, these findings are largely EU-centric and may not translate easily to contexts with different political or economic constraints.

Perissi and Jones (2022) assess the evolution of National Energy and Climate Plans across EU member states. While they find improved alignment with EU goals over time, they highlight a persistent lack of detail in implementation and performance measurement. Without metrics to evaluate real-world impacts, the effectiveness of these plans remains speculative.

The aviation sector, though not central to freight transport, offers cautionary lessons. Pérez-Calderón et al. (2021) demonstrate that larger airlines tend to be more eco-efficient under the EU Emissions Trading Scheme; however, overall sectoral gains are limited. Markov modeling predicts a decline in emissions efficiency due to structural and economic challenges, underscoring the need for diversified policy approaches.

Finally, Luè et al. (2016) provide a roadmap through the EU-funded REACT project. They emphasize short-term, cost-effective measures (e.g., congestion pricing, vehicle downsizing), mid-term investments in electric vehicles, and long-term systemic shifts, such as

integrated urban transport planning. However, the uptake of these strategies varies widely among member states, and their cumulative impact on emissions reduction remains poorly quantified.

While these studies contribute valuable insights, many lack integration between technological feasibility, economic viability, and social acceptability. Cost-benefit analyses are rare, and few studies offer dynamic assessments that capture the evolving nature of transport systems.

Our study addresses these gaps by integrating policy analysis within a forecasting framework, allowing us to assess not only the desirability but also the achievability of emission reduction strategies. We aim to bridge the gap between theoretical policy tools and actionable, context-sensitive strategies for decarbonizing freight transport.

Across these thematic strands, several key limitations emerge in the current literature. First, forecasting models are either too data-dependent or narrowly scoped, limiting their ability to inform broad policy. Second, modal shift research, while promising, is often regional and lacks scalable frameworks that consider real-world costs, cargo types, and transport distances. Third, policy studies are fragmented, with many failing to evaluate implementation outcomes or account for socio-economic constraints.

This study addresses these gaps through a multimodal, cross-country forecasting approach combined with scenario-based policy analysis, leveraging state-of-the-art AIML-based prediction methods. We examine how emissions from freight transport vary across modes and countries, assess the potential for modal shift within broader policy frameworks, and evaluate the likelihood of nations meeting their emission targets. By emphasizing prediction intervals and contextual strategy evaluation, our research offers a practical guide for policymakers seeking to decarbonize the freight transport sector.

## **Methodology**

### ***Data sources and variables***

Various data sources have been utilized for this research. The univariate data used to forecast the trajectory of emissions and evaluate whether a country would reach the Green Deal goals were adopted from the European Commission's Emissions Database for Global Atmospheric Research (Crippa et al., 2022). The data includes longitudinal measurements of annual carbon dioxide emissions for various countries from 1997 to 2021, measured in million tonnes, and comprises a breakdown of emissions by sector. To exclude the anomalous decrease in CO<sub>2</sub> levels during the COVID-19 pandemic (Le Quéré et al., 2020), we only utilized the data up to 2019. The transport sector's CO<sub>2</sub> emissions were used for this study to evaluate the possibility of countries reaching the European Green Deal goals by 2030. The measured values in this data are gathered and managed by the Joint Research Centre from various data sources to account for the total emissions made by countries and sectors. The records in this data are updated based on the reports provided by various countries. It is important to note that the origin of the CO<sub>2</sub> attributed to a country is based on regional and territorial considerations and assignments.

Furthermore, we aimed to investigate the origins of CO<sub>2</sub> emissions from freight transport. Specifically, we sought to investigate the proportion of emissions produced in the transportation sector that would be attributed to freight transport and how it would be distributed among its various modes. The information captured in this dataset measures maritime and rail freight transport (Organisation for Economic Co-operation and Development [OECD], 2023a) differently from inland freight indicators. However, we initially planned to utilize data offered by the OECD on freight transport (OECD, 2023b). Thus, we opted for using Eurostat's database (EUROSTAT, 2023), which included data on trade volume by air, sea (maritime and inland waterways), and inland (railways and road) freight transport for each country across several years. In the case of Australia, the modal distribution was obtained from

the annual statistics yearbook published by its respective department of transport (Bureau of Infrastructure and Transport Research Economics [BITRE], 2022). Moreover, the modal split of Turkey was obtained from the impact assessment report of its Ministry of Environment, Urbanisation and Climate Change (Directorate General of Environmental Impact Assessment Permit and Inspection, 2021).

The appeal of the gathered data was that the modal split was expressed as the percentage of total trade volume (measured as tonne-km); however, to derive the raw emissions for each transport mode, emission factors (measured as gCO<sub>2</sub>/tonne-km) were utilized for each mode. To incorporate the emission factors, information provided by the European Chemical Transport Association (ECTA) and the European Chemical Industry Council (CEFIC) in the Guideline for Measuring and Managing CO<sub>2</sub> Emissions from Freight Transport Operations (ECTA & CEFIC, 2021) was used. This allowed us to distribute emissions across different modes. Finally, by utilizing the population estimates from the World Bank dataset (World Bank, 2026), we controlled for the effect of countries' economic development and size on per capita emissions by transport mode. It is worth noting that although data were collected from multiple distinct sources, particular attention was paid to ensuring their compatibility. Specifically, historical emissions and emission factors were obtained directly from their respective sources, with values reported in consistent measurement units: million tonnes of CO<sub>2</sub> for emissions and grams of CO<sub>2</sub> per tonne-kilometer for emission factors. For the third source, the modal split data, values were compiled from various sources and harmonized by standardizing all figures to reflect the percentage share of total freight transport performance, measured in tonne-kilometers. In cases where the available data for a specific country were not reliably available or was reported inconsistently, those observations were excluded from the analysis. To ensure methodological coherence when deriving mode-wise emissions, all units and computational steps were carefully aligned to yield internally consistent outputs.

## ***Prediction***

By adopting an automated model selection framework, PyCaret's Python library (Ali, 2020) is utilized to train and compare a range of time series models, and to derive transport emission forecasts for countries up to 2030. In addition to providing various time series models, this package also automates the parameter selection for main types of analyses such as generalized least-squares (GLS) and generalized linear mixed models (GLMM), generalized additive mixed models (GAMM), autoregressive integrated moving average (ARIMA) and autoregressive integrated moving average with exogenous variables (ARIMAX) models, vector autoregression (VAR) and structural vector autoregressive models (SVAR), and vector error correction models (VECM) (Beard et al., 2019).

Before training and parameter selection, the data is scaled using a robust median-based scaling method to mitigate the effect of outliers (Lin et al., 2018). To equalize the variance (Milionis, 2022), approximate the underlying white noise to a normal distribution (Shumway & Stoffer, 2017), and facilitate the derivation of prediction intervals (Chatfield & Xing, 2019), apply box-cox and log transformations to the input data before training the models. The choice of whether to apply the transformation or which one to choose depends on the model's performance on the test set.

More specifically, to account for model-specific sensitivity to data distribution, three versions of the data for each country were prepared using no transformation, log transformation, and Box-Cox transformation (Box & Cox, 1964). Each version was independently fed into PyCaret's time series module, where all available models were trained and evaluated using a 4-fold expanding window cross-validation scheme. This approach enables temporal validation by simulating multiple historical forecasting scenarios. In this approach, models were iteratively trained on progressively larger subsets of the time series, beginning with an initial 10-year window and forecasting 11 years ahead in each fold.

Hyperparameter optimization for each model was carried out automatically by PyCaret's internal routines. From each country, the ten best-performing models, ranked by their average mean absolute percentage error (MAPE)<sup>1</sup> across the validation folds, the data were retained for further evaluation. These models were then assessed on a separate hold-out test set to evaluate their out-of-sample performance. The model yielding the lowest MAPE on this test set was selected as the final forecasting model for the respective country. No further retraining was performed; the forecasts and prediction intervals through 2030 were generated directly from this selected model<sup>2</sup>.

The prediction interval obtained from the best-performing model represents the range of values that the estimated CO<sub>2</sub> emissions are likely to take. Thus, by comparing it with the country's emission target and calculating the proportion of the forecasted emission range below the target level to the predicted emission interval, the country's probability of reaching and producing an emission level lower than the target for 2030 can be determined based on the current trend in the data. Consequently, if the country's emission range falls entirely below the target, the probability of reaching the Green Deal objective would be 1; conversely, if the emission range falls entirely above the target, the probability would be 0.

Moreover, the obtained point estimates of CO<sub>2</sub> emissions in the 2030s only reflect the total emissions of the transport sector. However, the question remains: To what extent does

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<sup>1</sup> The selection of the final forecasting model was based exclusively on MAPE due to its intuitive interpretability and comparability across countries of different emission scales. Other metrics, such as RMSE or MAE, while helpful, are sensitive to scale or unit and were not uniformly suitable across the diverse country profiles in our sample. MAPE's relative-error formulation allowed for consistent comparison and robust model ranking.

<sup>2</sup> The evaluated models included: Naive Forecaster, Grand Means Forecaster, Seasonal Naive Forecaster, Polynomial Trend Forecaster, ARIMA, SARIMA, SARIMAX, Auto ARIMA, Exponential Smoothing, STL Forecaster, Croston Forecaster, ETS, Theta Forecaster, TBATS, BATS, Prophet Forecaster, Linear with Conditional Deseasonalize & Detrending, Elastic Net with Conditional Deseasonalize & Detrending, Ridge, Lasso, Lasso Least Angular Regressor, Bayesian Ridge, Huber, Orthogonal Matching Pursuit, K Neighbors, Decision Tree, Random Forest, Extra Trees, Gradient Boosting, AdaBoost, Light Gradient Boosting, and CatBoost—all implemented with Conditional Deseasonalize & Detrending where applicable (For complete documentation, see: [https://pycaret.readthedocs.io/en/stable/api/time\\_series.html#pycaret.time\\_series.models](https://pycaret.readthedocs.io/en/stable/api/time_series.html#pycaret.time_series.models))

each mode of freight transport contribute to a country's total transport emissions? This distinction is vital, as each mode contributes disproportionately to the country's overall pollution, particularly given the significant differences in the average emission factors of each mode. To address this question while accounting for potential changes in freight transport structure, country-specific freight modal shares were projected to 2030 using historical modal split data. Specifically, we apply the compositional time-series forecasting framework proposed by Snyder et al. (2017), which accounts for the non-negativity and the total per-country shares equal to one constraints when forecasting. This approach allows modal shares to evolve gradually over the projection horizon while preserving the fundamental properties of the data and remaining consistent with observed long-term trends in each country's freight transport system.

The forecasted 2030 emissions were first converted to freight-only emissions by applying the average freight share from the transport sector, as reported by Ritchie (2020). These national freight emissions (in million tonnes of CO<sub>2</sub>) were then apportioned across transport modes using the projected modal shares for 2030. Since emission intensities differ significantly by mode, the projected trade share of each mode was weighted by its emission factor (in g CO<sub>2</sub>/tonne-km) to derive its proportional contribution to national freight CO<sub>2</sub>. These shares were then multiplied by the country's total freight CO<sub>2</sub> emissions to estimate mode-wise emissions. As mentioned earlier, the manual published by the European Chemical Transport Association and European Chemical Industry Council (ECTA & CEFIC, 2021) was utilized to incorporate emission factors. Due to data coverage constraints, countries such as the United States of America, Iceland, New Zealand, Japan, Mexico, and South Korea were excluded from this analysis.

To illustrate, the proportional contribution of freight mode  $j$  to total freight CO<sub>2</sub> emissions in country  $i$  is calculated as:

$$w_{ij} = \frac{s_{ij} f_j}{\sum_j s_{ij} f_j} \quad (1)$$

Multiplying  $w_{ij}$  by the country's forecasted 2030 freight CO2 emissions yields the CO2 amount attributable to mode  $j$ . Where  $s_{ij}$  is the share of mode  $j$  in country  $i$ 's total freight volume (as a percentage), and  $f_j$  is the average emission factor of mode  $j$  (in gCO2/tonne-kilometre).  $w_{ij}$  is a unitless weight indicating the proportional contribution of that mode to total CO2 emissions.

Since population size is one of the key drivers of transport-related emissions (Li & Li, 2026), countries with larger populations tend to exhibit higher absolute emission levels irrespective of their underlying freight transport structure. To isolate structural differences in modal emission patterns from scale effects, the projected 2030 freight modal emissions were normalized by population. Specifically, modal-specific freight CO2 emissions were divided by country-level population projections obtained from the World Bank (2026), yielding per-capita modal emission estimates. This normalization removes the confounding influence of country size and enables meaningful comparison of freight transport emission structures across countries with heterogeneous population levels. The countries with homogeneous estimated per-capita modal emission patterns were then identified by cluster analysis of the resulting data. A model-based approach was employed, and K-means clustering (Hartigan & Wong, 1979) was used to derive the results. Because the study follows a sequential framework, the output from the emission forecasts serves as the direct input for the clustering procedure, allowing countries to be grouped based on similarities in their projected per-capita modal emission profiles and facilitating the identification of policy-relevant clusters.

The optimal number of derived clusters is determined using the elbow method. The resulting clusters reveal countries requiring similar policies to meet Green Deal objectives. Finally, the modal split and transport mode emission distribution of the countries reaching the

2030s target and others are compared. The approach we have adopted and described is best summarized in Figure 1.

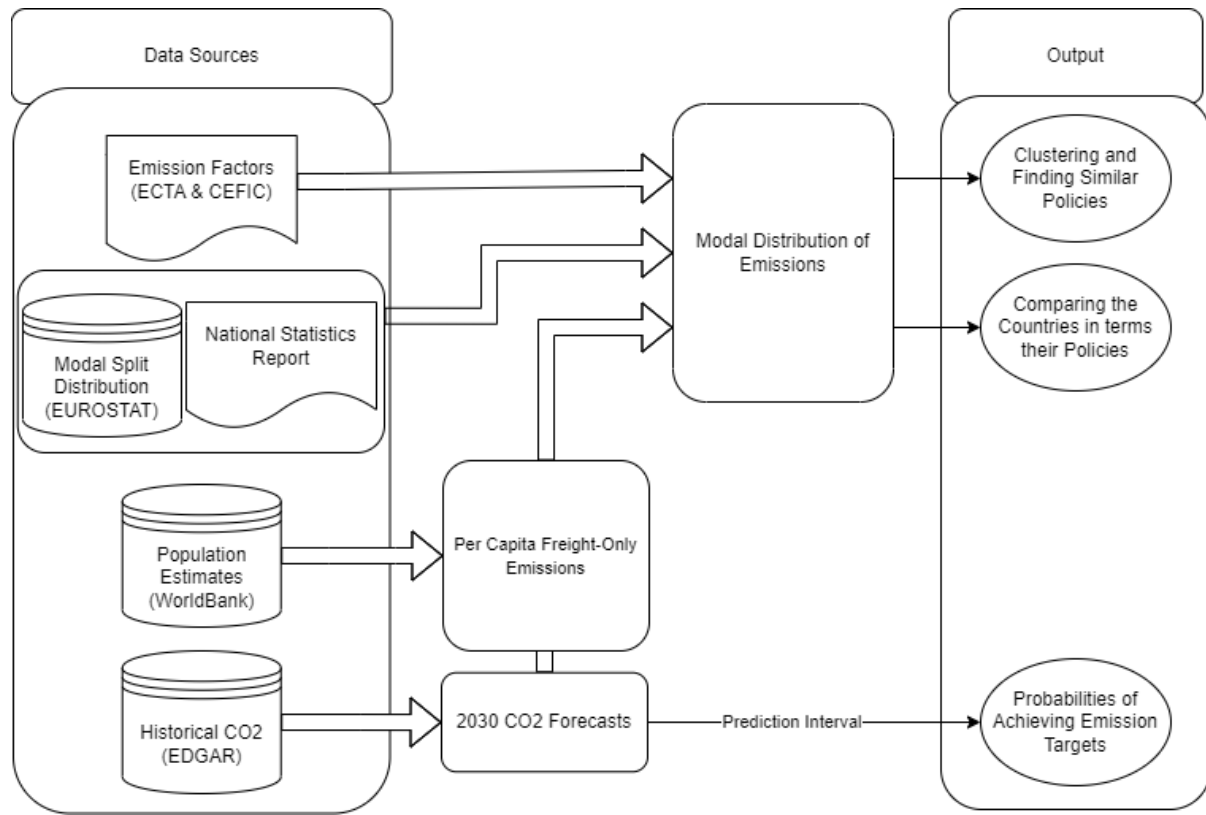


Figure 1: Process Flow

It is important to note that the double-counting problem does not affect our research. Double counting occurs when a greenhouse gas emission reduction or removal, measured using any mechanism, is accounted for more than once (Schneider et al., 2015). In our setting, the historical records used for forecasting have over-measured these historical observations. This means that the mean of the historical records should be lower, and the variance is also inflated in our data. However, since in our setting, we are not attempting to measure emissions but rather use machine learning to estimate future levels using the statistics reported by EUROSTAT, our approach would not further inflate the forecasts made in the future.

Furthermore, since the dataset is created following IPCC guidelines, the likelihood of double-counting is minimized. Although there are some discrepancies between this dataset (which measures CO2 data directly) and the alternative datasets (which report emissions in

terms of CO<sub>2</sub>eq), these differences arise from the use of different datasets for calculating the levels. More importantly, since the nature of our research involves comparing future emission possibilities (prediction interval) with previous emission levels in the 1990s and does not present a new measurement technique, double counting would have a minimal effect in our setting. If there were any double-counting in the data, the future estimations would be biased similarly. They would not affect our approach to comparing prediction intervals.

## Findings

After deriving the point forecasts and prediction intervals, they were compared with the Green Deal objectives (i.e., whether the forecasted interval includes 50% of the average 1990s emissions or values below) to determine the fraction that the predicted interval falls below the target emission level. Table 1 outlines the best-performing models, the MAPE corresponding to the best performing model, the target emission level, the forecast of CO<sub>2</sub> emissions for 2030, the confidence interval around the forecast, and the probability of achieving the target.

Table 1: Transport sector CO<sub>2</sub> emission estimates and the probability of achieving Targets

| Country   | Best Performing Model         | MAPE   | Target Emission | 2030 Forecast | Forecast Bounds    | Prob  |
|-----------|-------------------------------|--------|-----------------|---------------|--------------------|-------|
| Australia | AdaBoost                      | 0.53%  | 33.291          | 113.609       | [113.287, 116.222] | 0     |
| Austria   | AdaBoost*                     | 1.83%  | 7.960           | 28.702        | [27.097, 30.486]   | 0     |
| Denmark   | Naive Forecaster <sup>†</sup> | 13.93% | 5.720           | 12.185        | [9.781, 15.181]    | 0     |
| Finland   | ARIMA <sup>‡</sup>            | 7.08%  | 5.766           | 10.823        | [8.023, 12.554]    | 0     |
| France    | Naive Forecaster <sup>†</sup> | 2.09%  | 60.951          | 125.688       | [104.988, 150.469] | 0     |
| Germany   | Theta Forecaster <sup>‡</sup> | 1.77%  | 83.805          | 165.205       | [145.316, 180.892] | 0     |
| Greece    | Auto ARIMA <sup>†</sup>       | 24.64% | 8.550           | 9.9144        | [8.121, 12.104]    | 10.8% |
| Hungary   | ARIMA <sup>†</sup>            | 11.15% | 3.799           | 13.411        | [10.0943, 17.817]  | 0     |
| Ireland   | ARIMA <sup>‡</sup>            | 13.59% | 3.209           | 11.431        | [8.105, 15.999]    | 0     |
| Italy     | ETS <sup>‡</sup>              | 11.45% | 53.096          | 95.819        | [49.6567, 126.564] | 4.5%  |

| Country     | Best Performing Model                     | MAPE   | Target Emission | 2030 Forecast | Forecast Bounds    | Prob |
|-------------|-------------------------------------------|--------|-----------------|---------------|--------------------|------|
| Latvia      | Gradient Boosting <sup>*‡</sup>           | 9.14%  | 1.122           | 3.529         | [2.674, 4.014]     | 0    |
| Lithuania   | Bayesian Ridge <sup>*‡</sup>              | 12.38% | 1.905           | 6.202         | [5.253, 8.101]     | 0    |
| Luxembourg  | Decision Tree <sup>*</sup>                | 17.40% | 1.736           | 7.867         | [7.355, 10.504]    | 0    |
| Netherlands | Theta Forecaster <sup>‡</sup>             | 17.10% | 14.883          | 32.132        | [27.272, 36.393]   | 0    |
| Norway      | ARIMA <sup>‡</sup>                        | 4.91%  | 5.690           | 11.225        | [8.575, 13.593]    | 0    |
| Poland      | Theta Forecaster <sup>†</sup>             | 11.51% | 11.921          | 70.111        | [48.252, 101.871]  | 0    |
| Portugal    | Exponential Smoothing                     | 16.45% | 6.409           | 21.026        | [11.399, 29.069]   | 0    |
| Slovakia    | K Neighbours <sup>*‡</sup>                | 8.62%  | 1.858           | 9.824         | [5.481, 58.183]    | 0    |
| Slovenia    | K Neighbours <sup>*</sup>                 | 4.21%  | 1.717           | 6.683         | [6.185, 7.282]     | 0    |
| Spain       | Decision Tree <sup>*</sup>                | 30.41% | 36.797          | 112.129       | [104.089, 143.515] | 0    |
| Sweden      | ARIMA <sup>‡</sup>                        | 10.99% | 10.090          | 16.702        | [10.714, 19.788]   | 0    |
| Switzerland | Naive Forecaster <sup>‡</sup>             | 5.55%  | 7.360           | 15.762        | [13.437, 17.717]   | 0    |
| Turkey      | Orthogonal Matching Pursuit <sup>*†</sup> | 13.59% | 15.834          | 112.978       | [108.752, 146.565] | 0    |

\* These models internally apply conditional Deseasonalising and Detrending

† The input was log-transformed.

‡ The input was transformed using the Box-Cox method.

For example, in Table 1, the probability of Greece achieving the target emissions is 10.8%, and the probability of Italy achieving its target emissions is 4.5%. No other country has a positive probability of achieving their target emission levels.

### ***Sensitivity to COVID-19 Period***

To assess the robustness of our forecasting framework in light of the unprecedented COVID-19 pandemic, we conducted a post-hoc sensitivity analysis incorporating the actual CO2 emissions data from 2020 and 2021, which were excluded from the original training set to avoid anomalous pandemic-related distortions. Table 2 presents the percentage deviations of actual emissions from both the point forecasts and the lower bounds of the 95% prediction

intervals for 2020 and 2021 across a set of countries, calculated as  $(\frac{Forecast-Actual}{Actual})$ . Positive values indicate model over-prediction, while negative values indicate under-prediction.

Table 2: Percentage deviations of actual 2020 and 2021 CO<sub>2</sub> emissions from point forecasts and lower prediction bounds.

| Country     | 2020 % Deviation<br>from Forecast | 2020 % Deviation<br>from Lower Bound | 2021 % Deviation<br>from Forecast | 2021 % Deviation<br>from Lower Bound |
|-------------|-----------------------------------|--------------------------------------|-----------------------------------|--------------------------------------|
| Australia   | 21.78%                            | 19.47%                               | 20.08%                            | 17.68%                               |
| Austria     | 16.37%                            | 7.72%                                | 14.19%                            | 7.44%                                |
| Denmark     | 21.14%                            | 13.37%                               | 20.56%                            | 9.77%                                |
| Finland     | 12.10%                            | 4.53%                                | 12.49%                            | 1.45%                                |
| France      | 19.51%                            | 13.20%                               | 9.95%                             | 1.83%                                |
| Germany     | 11.68%                            | 6.20%                                | 12.69%                            | 5.89%                                |
| Greece*     | 19.00%                            | 7.16%                                | 10.32%                            | -5.08%                               |
| Hungary*    | 8.46%                             | -1.16%                               | 1.88%                             | -10.56%                              |
| Ireland*    | 16.79%                            | 5.16%                                | 14.54%                            | -1.24%                               |
| Italy       | 21.53%                            | 16.32%                               | 8.59%                             | 0.95%                                |
| Latvia*     | 17.41%                            | 6.62%                                | 16.32%                            | -9.36%                               |
| Lithuania*  | 3.65%                             | -19.69%                              | -2.14%                            | -21.37%                              |
| Luxembourg  | 26.36%                            | 17.72%                               | 25.46%                            | 16.93%                               |
| Netherlands | 10.49%                            | 3.34%                                | 10.78%                            | 2.03%                                |
| Norway*     | 8.80%                             | 0.88%                                | 8.06%                             | -3.08%                               |
| Poland*     | 7.12%                             | -8.03%                               | 0.57%                             | -16.56%                              |
| Portugal    | 27.20%                            | 11.68%                               | 25.29%                            | 5.43%                                |
| Slovakia*   | 4.00%                             | -40.54%                              | -3.19%                            | -42.65%                              |
| Slovenia    | 23.57%                            | 18.96%                               | 20.30%                            | 14.72%                               |
| Spain       | 28.50%                            | 21.60%                               | 17.47%                            | 11.29%                               |
| Sweden*     | 13.85%                            | 2.65%                                | 12.05%                            | -4.01%                               |

| <b>Country</b> | <b>2020 % Deviation<br/>from Forecast</b> | <b>2020 % Deviation<br/>from Lower Bound</b> | <b>2021 % Deviation<br/>from Forecast</b> | <b>2021 % Deviation<br/>from Lower Bound</b> |
|----------------|-------------------------------------------|----------------------------------------------|-------------------------------------------|----------------------------------------------|
| Switzerland    | 20.39%                                    | 15.40%                                       | 19.76%                                    | 12.65%                                       |
| Turkey         | 13.09%                                    | 9.85%                                        | 12.04%                                    | 8.49%                                        |
| <b>Average</b> | <b>16.21%</b>                             | <b>5.76%</b>                                 | <b>12.52%</b>                             | <b>0.11%</b>                                 |

\* Countries whose emissions fall within the model's prediction bounds.

The results indicate a consistent pattern of over-prediction by the forecasting models during the pandemic years. Specifically, the point forecasts for 2020 and 2021 exceeded the actual reported emissions by approximately 10% to 28% for most countries, with deviations from the lower bounds generally smaller but still positive. This systematic overestimation reflects the fact that the models did not explicitly capture the sharp, temporary reductions in emissions caused by pandemic-induced restrictions, such as lockdowns and travel limitations. However, despite this over-prediction, the actual emission values for some of the countries remain close to or within the forecast intervals, demonstrating the resilience of emissions even in the presence of exogenous events with global effects, albeit without accounting for the pandemic-related shock.

It is essential to note that these deviations reflect the model's inability to accurately predict the pandemic's impact, since it was trained exclusively on pre-pandemic data, rather than a failure to capture underlying emission trends. The dip in 2020 emissions can be regarded as a transient shock rather than a structural break in long-term trajectories. Indeed, emissions began to rebound in 2021, moving closer to model predictions, which suggests that the forecasting approach remains relevant for monitoring recovery scenarios. Rather than myopic, the models are arguably conservative, leaning towards upward forecasts that emphasize a return to pre-pandemic emission levels and potentially reflect the resilience of transport emissions against short-term disruptions. This underscores that while the forecasts should be interpreted

with caution during extraordinary events, they provide a robust baseline for policy evaluation and strategic planning.

### ***Predictions for individual countries***

The forecasts from the models indicate that among the 23 countries considered in this study, only two countries have the potential to reach the goal. The estimates, which reflect the current trajectory of the countries' emissions and underlying policies, elucidate that many countries are likely to miss the emission reduction objective (See the Appendix for point predictions and prediction intervals for each country). Of the analyzed candidates, only Greece and Italy exhibit a chance to reach and exceed their target objective in 2030. Moreover, the findings suggest that a vital policy reform is required among the studied countries to achieve their emission reduction objectives.

Given the current emissions landscape and CO<sub>2</sub> emission trajectories, only two countries are likely to reach the 50% reduction goal. However, it does not necessarily mean that other countries are not on the path to achieving this goal, either by setting a more lenient CO<sub>2</sub> reduction target or by extending the period. The prediction intervals revealed above allow us to investigate this and compare alternative reduction percentages against each country's CO<sub>2</sub> forecast interval. Hence, we can discuss how much of the European Green Deal targets these countries can achieve by 2030. For instance, a country might not be likely to meet a 50% reduction goal by 2030, but it might be likely to achieve a 40% reduction goal. To that end, we examined different emission reduction percentages, considering 1990s levels of emissions as the goal (since only two countries are likely to achieve the target with a 50% reduction, we set the upper bound at 50%). We then compared these percentages with 2030 prediction intervals for each country. Results indicated that among the 23 countries analyzed, only 11 (9 countries excluding Greece and Italy) showed a possibility of reaching the emission reduction goals with

targets lower than a 50% reduction. In other words, the forecast interval for the remaining 12 countries was above the levels of the 1990s. Based on this analysis, not only are these countries unlikely to decrease their emissions, but they are also expected to increase them by 2030 compared to the levels of the 1990s. A summary of these results is presented in Table A.1.

Figure 2 provides a visual summary of the number and types of countries that can achieve the target goals with various fractions of 1990s emissions. While Table 1 shows in the very right column the probability of achieving the target emissions, which is half of the levels in 1990s, Figure 2 shows what fraction of the target emissions each country can achieve. It is a summary of Table A.1 which shows the highest percentage reduction achievable by each country in 10% bands after 50% reduction. The percentages reported in Figure 2 are complements of the reduction percentages reported in Table A.1. For example, Switzerland can reduce its carbon emissions at most to 8.7% of its level in 1990s. So, it will be within 90%-100% of its 1990s levels.

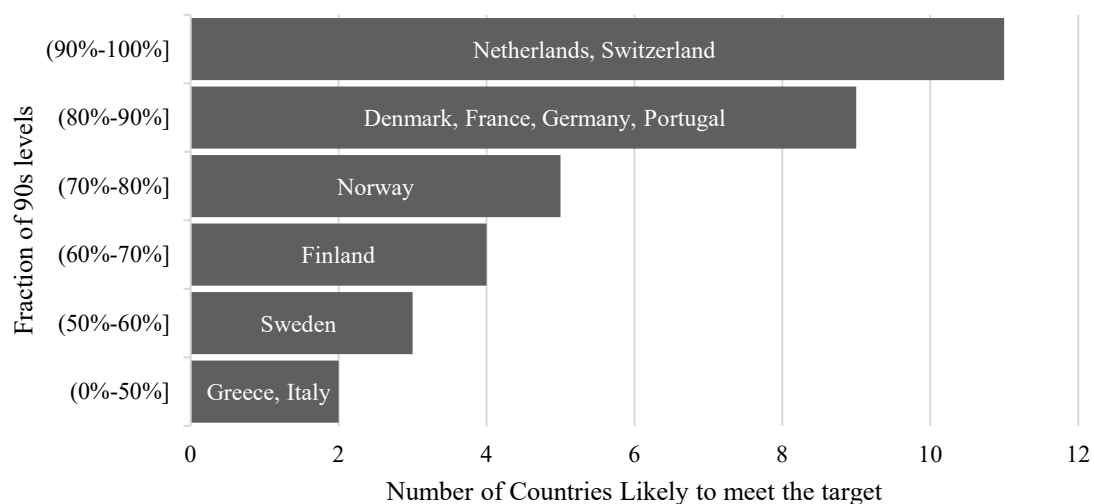


Figure 2: Countries likely to achieve 2030 emission reduction goals with different targets  
(fraction of CO<sub>2</sub> compared to 90s levels)

For example, in Figure 2, Greece and Italy are the only two countries that can achieve half of the 1990s emission levels. Sweden can achieve somewhere more than 50% up to 60%

of its emissions in 1990s. Finland can reduce its emissions to more than 60% up to 70% of 1990s levels. Norway can reduce its emissions to more than 70% up to 80% of its levels in 1990s. Denmark, France, Germany, and Portugal could reduce their emissions to more than 80% up to 90% of their levels in 1990s. Finally, Netherlands and Switzerland could reduce their emissions to more than 90% to 100% of their emissions in 1990s. No other country has any probability of reaching their emission levels in 1990s; they will have much more emissions than they had back in the 1990s.

### ***Clusters of countries concerning their modal emissions***

After forecasting and synthesizing the modal freight emission distributions per capita for the focused countries and their predicted 2030 emissions, the distributions were clustered using the k-means algorithm. The optimal number of clusters was selected based on the elbow method (Ketchen and Shook, 1996), using the within-group sum of squares plot to identify the point at which the number of clusters experienced its first significant decrease. Figure 3 illustrates the results obtained using the elbow method.

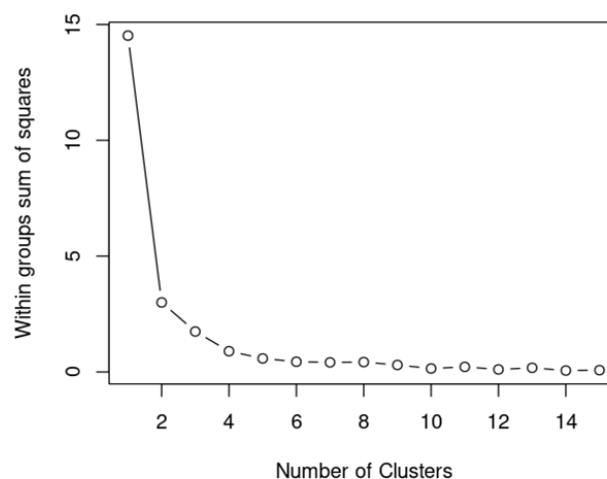


Figure 3: Within-Group Sum of Squares Results for Each Cluster Number Selected for Grouping the per Capita Modal CO2 Emissions

We tested 2, 3, 4, and 5 clusters for the data. The best cluster solution was obtained with 3 clusters. When we fit a kmeans model with 2 clusters, the model separates the data into two sets: one with 22 countries and the other with 1 (Luxembourg). Since separating the data into two such clusters single out Luxembourg, we conclude this is not a good cluster solution. When we fit a kmeans model with 3 clusters, we have three sets of countries with 9, 1, and 13 observations in each cluster. The quality of clustering is measured as "between-group sum of squares / total sum of squares" (higher values of this measure signal better clustering quality). The partition quality with 2 clusters is 79.33% whereas segmenting the countries into three clusters results in a partition quality of 87.97%. Hence, we conclude three clusters is the best partition of these countries. In cluster analysis, silhouette shows how objects are positioned within their cluster (Rousseeuw, 1997). We evaluated the clustering quality by combining the silhouettes into a single plot in Figure 4 with the average silhouette of 0.32 given as the horizontal dashed line.

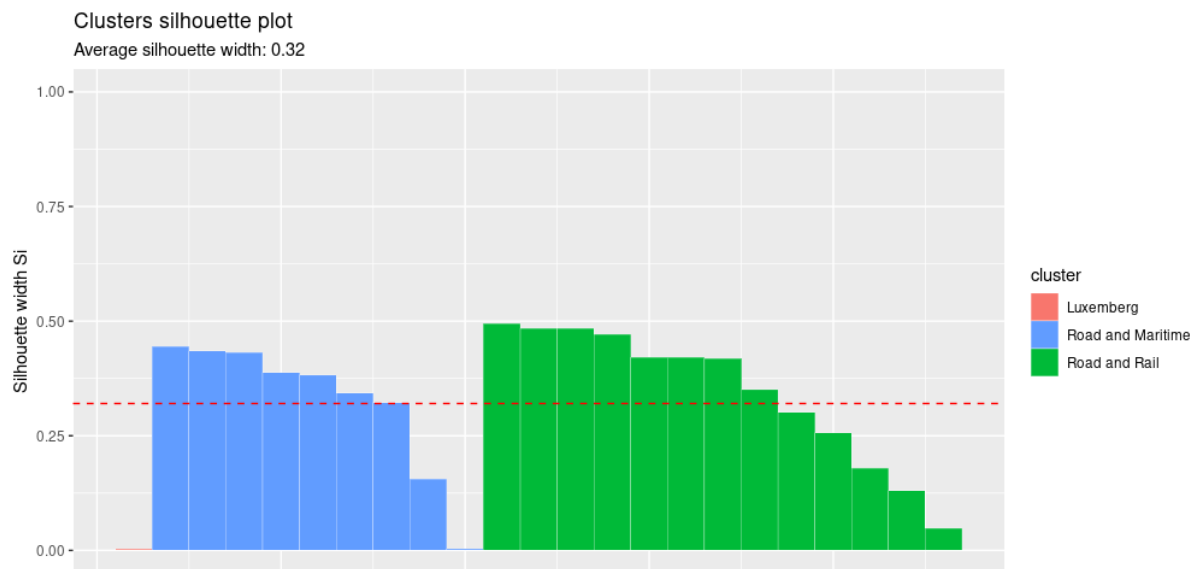


Figure 4: Silhouette scores of countries in clusters

Segmenting the countries revealed three clusters: the first cluster had ten countries (Denmark, Greece, Ireland, Italy, Netherlands, Norway, Portugal, Spain, Sweden), the second

cluster included twelve countries (Austria, Finland, France, Germany, Hungary, Latvia, Lithuania, Poland, Slovakia, Slovenia, Switzerland, Turkey, and Australia), and the last cluster had only one country (Luxembourg). Grouping countries based on their respective per capita modal emissions distribution revealed that members of the first cluster had high road and maritime emissions. In contrast, the countries assigned to the second cluster had high road and rail emissions per capita (Figure 5). Hence, the first cluster is named road and maritime, whereas the second cluster is named road and rail. Luxembourg is unlike any other country, as shown in the modal freight emissions in Table 3.

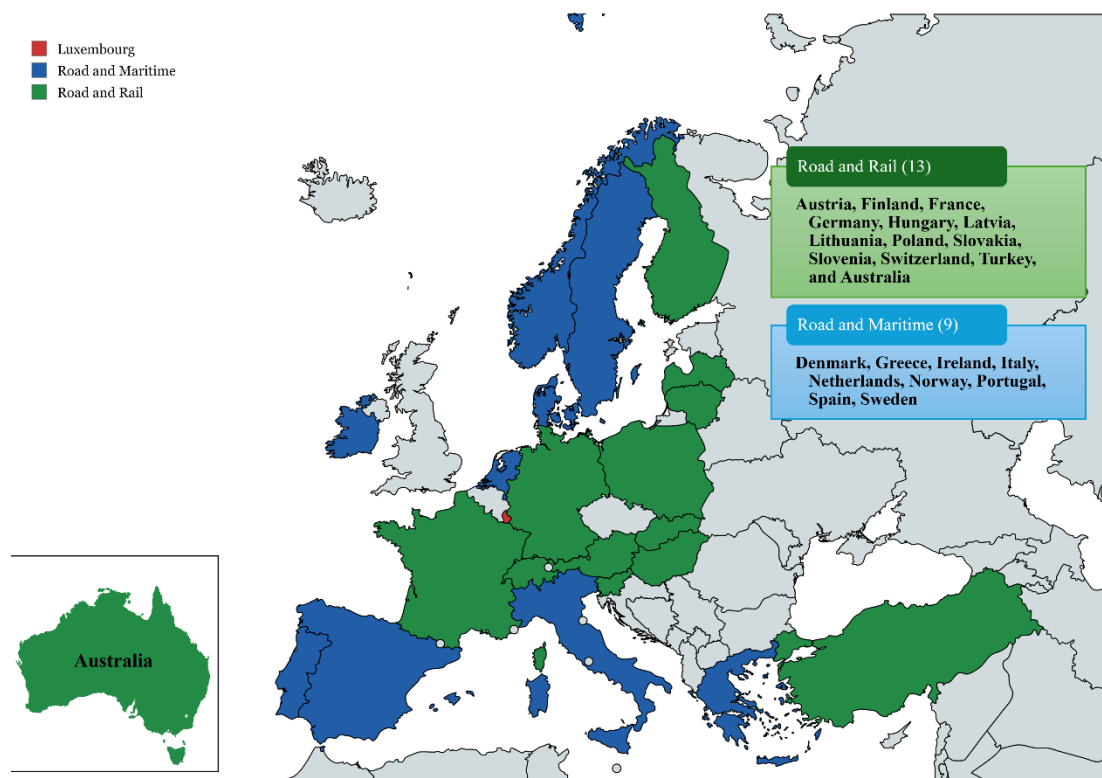


Figure 5: Assignment of Countries to Their Respective Cluster by Colour on the Map

The countries in the Road and Maritime cluster have comparable maritime and road transport policies. For example, Denmark focuses on the green transition of the transport sector, focusing on electrification, eco-driving, and digital logistics (Denmark Ministry of Transport, 2025). In this cluster, Netherlands, Norway, and Spain have advanced strategies for low-carbon

freight transport. Greece and Portugal focus on port-hinterland connectivity. While all countries have strong integration with the TEN-T corridor, few (Greece, Latvia, and Portugal) heavily rely on EU funding to sustain connectivity.

The countries in the Road and Rail cluster are characterized by the strong emphasis on rail transport policies. Austria, Switzerland, Germany, and Poland promote rail freight strongly. Across all countries in this cluster, road transport is overwhelmingly the major cause of CO<sub>2</sub> emissions from transport. While there is a desire to shift transport to rail and investments in line with that desire, the realized use of rail in transport sector is yet to increase to have meaningful reductions in carbon emissions. Especially Germany, France, Switzerland, and Austria reduce transport emissions with policies that incentivize electric vehicle adoption and new investments in the rail infrastructure.

Luxembourg was grouped into a single cluster during the clustering process. This is because the country has a low population compared to others and high road transport activity, but low rail transport activity compared to countries in the Road and Rail cluster. Being a land-locked country, it is dissimilar to those countries in the Road and Maritime cluster as well; hence it is quite different from any other country included in the dataset. Despite having the smallest population, Luxembourg had the highest per capita emissions from freight transport. Therefore, a high per capita road freight does not necessarily mean that this country is the largest air polluter due to road freight. Instead, it indicates that the amount of CO<sub>2</sub> emitted per capita in road freight transport is very high in Luxembourg, making it an outlier among other countries.

Table 3 summarizes the mean per capita emissions from each mode of transport in each cluster.

Table 3: Mean Freight Emissions per Capita per Transport Mode in Each Cluster

| Group           | Air  | Railways | Roads | Maritime | Inland Waterways |
|-----------------|------|----------|-------|----------|------------------|
| Road & Maritime | 0.04 | 0.02     | 0.41  | 0.35     | 0.01             |
| Road & Rail     | 0.08 | 0.14     | 0.75  | 0.03     | 0.00             |
| Luxembourg      | 0.84 | 0.08     | 3.99  | 0.00     | 0.08             |

Figure 6 presents the main differences between the first two clusters in each mode with box plots.



Figure 6: Comparison of per capita CO2 emissions of each mode for the two clusters

Generally, the countries in the first cluster, denoted by Road and Maritime, exhibit relatively high emissions per capita in road and maritime transport modes in the context of freight transport emissions. Interestingly, Greece and Italy are countries<sup>3</sup> that will likely reduce their emissions by at least 50% by 2030, and they are both in the Road and Maritime cluster. This suggests that the policies adopted, and measures implemented by countries in this cluster

<sup>3</sup> Four more countries with a chance of reaching a lowered emission target with reductions less than 50% also belong to this group.

provide them with inherent advantages that contribute to their higher likelihood of emissions. Specifically, these countries heavily utilize maritime freight transport, which has a relatively lower emission factor compared to other methods. Leaning on and prioritizing this mode has provided an advantage to be more environmentally sustainable. Thus, implementing practices that encourage moving away from modes with high emission factors leads to more environmentally friendly policies within their transportation sectors. Road transport remains the dominant mode of freight transport, with the second-highest average emission factor among all modes of freight transport. Road transport mode is also one of the most challenging modes to move away from.

On the other hand, the countries assigned to the Road and Rail cluster generally have high CO<sub>2</sub> emissions from road and rail (road being much higher than rail) in terms of modal freight distribution. Although members of this cluster have higher rail freight CO<sub>2</sub> emissions per capita on average, road transport emissions are high across all clusters. In this cluster, they overshadow those of other transport modes. It is believed that these countries' heavy reliance on road transportation (including Luxembourg from its own cluster) is the cause of their inability to achieve the 2030 goals.

Considering this assignment and the countries that have a chance of meeting the European Green Deal objectives, one can suggest leaning toward transport modes with lower average emission factors and opting for more sustainable, environmentally friendly modes. Moreover, reducing reliance on transport modes with higher emissions (e.g., vessels with higher average emission factors, i.e., air and road) could improve their chances of achieving the 2030 target goals.

We use the null-hypothesis framework to compare their median per capita freight emissions across transport modes, providing an alternative perspective on how these clusters differ in their mode-specific emissions. Table 4 summarizes these results.

Table 4. Comparison between Clusters (Road and Maritime vs. Road and Rail)

|                  |                | <b>Statistic</b> | <b>Df</b> | <b><i>p</i></b> | <b>Mean Difference</b> | <b>SE difference</b> |
|------------------|----------------|------------------|-----------|-----------------|------------------------|----------------------|
| Inland waterways | Student's t    | 1.01             | 20        | 0.324           | 0.0108                 | 0.0107               |
|                  | Mann-Whitney U | 46               | -         | 0.369           | -2.88e-6               | -                    |
| Maritime         | Student's t    | 5.76             | 20        | < .001          | 0.3174                 | 0.0551               |
|                  | Mann-Whitney U | 1                | -         | < .001          | 0.318                  | -                    |
| Roads            | Student's t    | -3.6             | 20        | 0.002           | -0.3457                | 0.096                |
|                  | Mann-Whitney U | 10               | -         | < .001          | -0.2653                | -                    |
| Railways         | Student's t    | -2.1             | 20        | 0.049           | -0.1167                | 0.0557               |
|                  | Mann-Whitney U | 9                | -         | < .001          | -0.0637                | -                    |
| Air              | Student's t    | -1.46            | 20        | 0.159           | -0.0452                | 0.0309               |
|                  | Mann-Whitney U | 26               | -         | 0.032           | -0.0395                | -                    |

In Table 4, we can see that the two clusters differ significantly in maritime ( $U = 1$ ;  $p < 0.001$ ), road ( $U = 10$ ;  $p < 0.001$ ), railways ( $U = 9$ ;  $p < 0.001$ ) freight transport mode emissions per capita. Considering the direction of the differences, the Road and Maritime cluster has higher maritime-related emissions, while the Road and Rail cluster has significantly higher emissions from rail and road. Moreover, although both clusters exhibit high and significantly different road emissions, their primary distinction lies in maritime and rail emissions. Finally, since countries in Road and Maritime exhibit a higher probability of reducing emissions, it would be advantageous for other countries to investigate the transport policies of these countries.

## Discussion and Conclusion

This study offers a comprehensive, multi-country perspective on the transport sector's trajectory toward achieving the EU's 2030 climate goals. Our machine learning forecasts

indicate that only Greece and Italy are currently on track to meet their emission-reduction targets, while the remaining countries are falling behind. These findings not only underscore the ambitious nature of the European Green Deal but also point to fundamental structural and policy misalignments that hinder meaningful progress.

A key insight from our modal clustering analysis is that countries with a more balanced or maritime-heavy freight transport profile, such as Greece and Italy, are more likely to align with the 2030 goals. This suggests that reducing dependence on road freight (one of the modes with the highest average CO<sub>2</sub> emission factors) is critical to decarbonization. For a country, such a reduction in reliance on road freight necessitates, first of all, infrastructure investments. Countries need to expand and modernize their rail networks to make rail freight a competitive alternative. This includes enhancing intermodal terminals, improving rail logistics corridors, and electrifying freight lines. Countries will also need regulatory frameworks. For this purpose, governments could implement access charges, urban delivery restrictions, and emission-based tolling that disincentivize high-emission road transport, especially in dense urban areas. Additionally, subsidies and incentives will be necessary. Providing financial support for companies to switch to rail, maritime, or combined transport modes can help shift modal preferences. Similarly, tax exemptions for green logistics solutions or carbon-adjusted freight rates can promote modal shift.

Identifying the need for a modal shift is only the first step. To translate these findings into practical terms, policymakers must implement a targeted portfolio of interventions. Based on our analysis, countries in the "Road and Maritime" cluster, such as Greece and Italy, benefit from their reliance on maritime freight transport, resulting in a lower emission factor. Therefore, we recommend that countries, particularly those in the "Road and Rail" cluster, consider investing in maritime and rail infrastructure. For countries heavily reliant on road transport, inadequate infrastructure for alternatives is often a primary barrier to

decarbonization. Policymakers should expand port capacity, improve the efficiency of port-railway connections, and modernize rail networks. This would make maritime and rail transport more reliable, faster, and economically competitive with road haulage. Additionally, reforms can be implemented in road freight taxes, carbon pricing, and congestion pricing. Accordingly, governments must introduce road freight taxes to penalize more polluting vehicles as well as increase carbon taxes on fossil fuels used in transport. These precautions create an incentive to switch to cleaner fuels and less carbon-intensive transport modes. Beyond infrastructure and taxes, direct incentives such as subsidy programs, green logistics grants, or tax credits for freight operators that shift from road to rail or sea could be established. In other words, policymakers should incentivize the adoption of low-emission technologies, such as electric and hydrogen-powered freight vehicles, and support research and development for cleaner fuels.

By implementing these targeted interventions, countries can better align their transportation policies with the European Green Deal objectives and improve their chances of achieving climate neutrality. Future research should investigate the cost-effectiveness of these propositions and their real-world impacts to further refine policy recommendations. Additionally, fuel standards and fleet modernization will be needed. Setting stricter emissions standards for trucks or phasing in zero-emission freight vehicles would reduce the environmental impact of road transport while indirectly encouraging alternatives. Thus, reducing road freight dependency is not merely a modal adjustment, but it requires a multi-pronged policy ecosystem involving fiscal, regulatory, and infrastructural tools.

We suggest using the Principal-Agent Theory to explain the gap between policy ambition and implementation. In this context, the “principal” is the supranational policy-setting body (e.g., the European Commission), which establishes emissions targets. At the same time, the “agents” are individual nation-states responsible for implementing measures to achieve

these goals. This theory helps us understand why some countries fail to comply with the EU's emission targets, mainly due to the principle of information asymmetry. The principal cannot fully monitor or verify the execution of national policy, creating space for strategic inaction or symbolic compliance. Another issue is misaligned incentives. Countries with lower GDP per capita or limited freight alternatives may perceive the cost of compliance as higher than the perceived collective benefit. Another potential issue is the moral hazard. Agents may commit to goals (e.g., Green Deal targets) without credible enforcement mechanisms, banking on the assumption that penalties for noncompliance will be minimal or politically unfeasible.

To better align incentives, performance-based funding, peer benchmarking, or cross-border infrastructure subsidies could help address this gap. Principal–Agent Theory thus offers a valuable lens through which to analyze the persistent challenge of translating supranational commitments into national actions.

Like all forecasting studies, this work is subject to several limitations that should be acknowledged. Our modal freight emission estimates are driven by forecasting the freight modal split using available historical data, reflecting the implicit assumption that these modal shares evolve naturally over time. In reality, modal distributions may change due to technological advances, new policies, or external shocks (e.g., pandemics, wars). Even modest policy changes or shocks can shift modal shares, such as reductions in road freight activity in favor of rail or inland waterway transport, leading to notable changes in emissions profiles across countries. While the current assumption enables consistent comparison, it limits the ability to capture such modal transition effects, which may under- or over-estimate future emissions for specific modes and countries. Additionally, due to data unavailability—particularly on modal splits and freight-specific CO<sub>2</sub> emissions—we excluded countries such as the United States, Japan, South Korea, and others. As a result, the findings are limited in their global generalizability and primarily focused on Europe and select OECD members. The

models forecast emissions based on historical data trends, without accounting for future policy shocks or structural disruptions. Countries that introduce transformative climate measures post-2019 may deviate significantly from the trajectories we project. While we focus on sector- and modal-level emissions, we do not incorporate firm- or regional-level heterogeneity. Micro-level logistics innovations or subnational infrastructure strategies are therefore not captured in this analysis. The study uses fixed emission factors by transport mode, which may become inaccurate over time. Technological advancements, electrification, and cleaner fuels can significantly alter these factors.

Future research could address these limitations by incorporating dynamic modal shifts, exploring scenario-based forecasts, and expanding the model to include cost-effectiveness analysis of policy alternatives.

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The authors declare no competing interests.

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## Appendix:

Table A.1: How much can the countries achieve the targets?

| Countries   | 1990 Levels | 2030 Prediction | lower | upper | Highest % decrease achievable compared to 90s levels |
|-------------|-------------|-----------------|-------|-------|------------------------------------------------------|
| Australia   | 66.6        | 113.7           | 113.3 | 116.2 | -                                                    |
| Austria     | 15.9        | 28.7            | 27.1  | 30.5  | -                                                    |
| Denmark     | 11.4        | 12.2            | 9.8   | 15.2  | 14.5%                                                |
| Finland     | 11.5        | 10.8            | 8.0   | 12.6  | 30.4%                                                |
| France      | 121.9       | 125.7           | 105.0 | 150.5 | 13.9%                                                |
| Germany     | 167.6       | 165.2           | 145.3 | 180.9 | 13.3%                                                |
| Greece      | 17.1        | 9.9             | 8.1   | 12.1  | 52.5%                                                |
| Hungary     | 7.6         | 13.4            | 10.1  | 17.8  | -                                                    |
| Ireland     | 6.4         | 11.4            | 8.1   | 16.0  | -                                                    |
| Italy       | 106.2       | 95.8            | 49.7  | 126.6 | 53.2%                                                |
| Latvia      | 2.2         | 3.5             | 2.7   | 4.0   | -                                                    |
| Lithuania   | 3.8         | 6.2             | 5.3   | 8.1   | -                                                    |
| Luxembourg  | 3.5         | 7.9             | 7.4   | 10.5  | -                                                    |
| Netherlands | 29.8        | 32.1            | 27.3  | 36.4  | 8.4%                                                 |
| Norway      | 11.4        | 11.2            | 8.6   | 13.6  | 24.6%                                                |
| Poland      | 23.8        | 70.1            | 48.3  | 101.9 | -                                                    |
| Portugal    | 12.8        | 21.0            | 11.4  | 29.1  | 11.1%                                                |
| Slovakia    | 3.7         | 9.8             | 5.5   | 58.2  | -                                                    |
| Slovenia    | 3.4         | 6.7             | 6.2   | 7.3   | -                                                    |
| Spain       | 73.6        | 112.1           | 104.1 | 143.5 | -                                                    |
| Sweden      | 20.2        | 16.7            | 10.7  | 19.8  | 46.9%                                                |
| Switzerland | 14.7        | 15.8            | 13.4  | 17.7  | 8.7%                                                 |
| Turkey      | 31.7        | 113.0           | 108.8 | 146.6 | -                                                    |



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## **Trade flows and carbon emissions: how far are we from the climate targets?**

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