

Article

Identifying the Key Determinants of Road Transport CO₂ Emissions in a High-Altitude Region: Evidence from Qinghai, China

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Abstract

Road transport is an important source of carbon emissions worldwide, yet the factors driving these emissions may differ under varying geographical conditions. Plateau regions are characterized by high altitude and strong spatial constraints, but their transport carbon emission mechanism remains insufficiently understood. Taking Qinghai Province on the Qinghai–Tibetan Plateau as a case, this study estimates road transport CO₂ emissions from 2003 to 2022 using annual statistical data. It constructs a multidimensional indicator system covering economic development, industrial structure, energy use, and road transport activity, and applies correlation analysis, PCA, and LASSO regression to diagnose variable relationships and identify key drivers. The results show that GDP, VATSP, CVO, and TPT have stable positive effects on road transport CO₂ emissions, indicating that economic expansion, transport services, vehicle ownership, and passenger mobility are the dominant drivers. Industrial and energy-related variables have more indirect and stage-dependent effects: NMI and NFMO are negatively associated with emissions, whereas NMEC has a weak positive effect. These findings suggest that, under the dispersed spatial development and long-distance transport dependence of plateau regions, emissions are more directly shaped by economic and transport activity than by short-term changes in energy structure. Low-carbon transport policy in Qinghai should therefore combine transport-demand management, more efficient transport organization, public-transport improvement, and gradual transport electrification. The results provide evidence for emission-reduction strategies in high-altitude and ecologically fragile regions.

Keywords: road transport emissions; Qinghai–Tibet Plateau; LASSO; Third Pole; spatial constraints; low-carbon transport

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1. Introduction

Global climate warming has become an important and serious issue that threatens human survival, and this situation has driven the international community to reach a broad and shared consensus on reducing emissions [1]. Under the framework of the United Nations Framework Convention on Climate Change, countries have successively

proposed emission reduction targets, but global fossil energy CO₂ emissions have continued to increase, which indicates that existing measures are still not sufficient to offset the pressure caused by the growing demand for energy [2]. In this context, the transport sector has become one of the fields where carbon emissions are growing relatively rapidly. The International Energy Agency's 2023 report points out that carbon emissions from the transport sector have increased by about 240 Mt CO₂, and the main reason for this increase lies in the continuous expansion of transport demand [3]. Existing studies have shown that carbon emissions from the transport sector are not only influenced by economic development, energy use, and industrial activities, but are also closely related to regional spatial structure and the layout of transport systems [4,5]. This is mainly reflected in the fact that land use and the spatial distribution of economic and industrial activities affect the scale of transport demand, travel distance, and transport activity, which in turn influence transport CO₂ emissions. Therefore, reducing emissions in the transport sector is not only an issue related to energy or technology, but is also closely associated with regional development patterns and organization of transport systems. On the Qinghai–Tibetan Plateau, this issue is more pronounced and more evident. Qinghai Province, located in the northeastern part of the Qinghai–Tibet Plateau, is constrained by high altitude, complex terrain, and ecological protection requirements. As a result, developable land resources are limited, while population and economic activities are spatially dispersed, making regional development highly dependent on long-distance road transport. At the same emission level, plateau regions face greater ecological and environmental pressure [6–8]. The Qinghai–Tibetan Plateau, known as the “Third Pole of the World”, is an important source area for many transboundary rivers, and damage to its ecological environment can lead to glacier retreat. The instability of the water system may increase the occurrence of extreme disasters such as floods and droughts in downstream areas, and may pose potential threats to agricultural production, hydropower development, and regional water resource security, thereby affecting the water resources and ecological security of downstream regions in China as well as countries in South Asia and Southeast Asia [9]. Therefore, in this context, the relationships among transport demand, transport activities, and carbon emissions are more complex, and the carbon issue is more severe, which may be different from that in other regions. Therefore, the core question addressed in this study is: in high-altitude regions, what are the main driving factors of carbon emissions from road transport, and are their underlying mechanisms different from those observed in general regions?

Existing studies generally hold that carbon emissions from the transport sector are mainly influenced jointly by factors such as economic growth, energy consumption, and industrial structure [4]. Among these factors, economic growth usually expands transport demand, promotes increases in both the scale of transportation and the intensity of transport activities, and thereby leads to a rise in carbon emissions, and this process is often reflected in the growth of transport turnover [10]. In terms of energy, although the optimization of the energy structure helps to reduce overall carbon emissions, in the transport sector, carbon emissions still mainly come from the combustion of fossil fuels such as gasoline and diesel, and clean energy has not yet achieved large-scale substitution, so its emission reduction effect remains relatively limited [11,12]. At the same time, industrial structure further affects carbon emissions from the transport sector by influencing the scale and modes of transport demand across different industries [13]. Overall, there are complex interaction relationships among the economy, energy, and industry, and their impact pathways still lack a unified and widely accepted understanding [14]. In terms of methodology, existing studies mostly adopt the STIRPAT model and its extended forms, and combine them with scenario analysis to examine the driving factors of carbon emissions at the national or regional level [15,16]. In recent years, with the improvement of data analysis capabilities, some studies have begun to introduce machine learning

methods such as XGBoost, Random Forest, and LASSO regression to identify the importance of variables and to capture more complex relationships [17–19]. Overall, existing studies have conducted systematic analyses of the factors influencing carbon emissions in the transport sector from multiple dimensions and have obtained relatively consistent conclusions in plain regions or in large cities. However, the above findings are largely derived from studies conducted in plain regions or large cities. In these areas, population, industry, and economic activities are usually highly concentrated, and transport carbon emissions are jointly influenced by factors such as economic growth, population size, industrial structure, and energy use [20]. Meanwhile, a recent study of 274 Chinese cities found a significant positive relationship between urban expansion and transport carbon emissions, suggesting that land development patterns and changes in spatial structure can also influence transport carbon emissions [21]. In contrast, high-altitude regions are often affected by complex terrain, ecological conservation requirements, and limited land development opportunities. As a result, population and industrial activities tend to be more dispersed, and regional development is generally more dependent on long-distance road transport. Previous studies in regions such as the Yunnan Plateau and the East African Plateau have suggested that the relationship between transport activities and carbon emissions in high-altitude regions may be further influenced by regional development patterns and transport conditions [22,23]. As a result, the dominant drivers of transport carbon emissions and the strength of their effects may vary considerably across regions. Therefore, it remains unclear whether findings derived from plain regions can be directly applied to high-altitude and ecologically fragile areas such as Qinghai, and systematic evidence is still limited.

Taken together, existing research has identified economic growth, energy use, industrial structure, and transport activity as important drivers of transport emissions, but the relative importance and pathways of these drivers remain unclear in high-altitude, ecologically fragile regions. In such regions, developable land is limited, settlements and industries are dispersed, and road transport often becomes the main link between resource areas, production sites, markets, and tourism destinations. This study therefore asks whether road transport CO₂ emissions in Qinghai Province from 2003 to 2022 were driven primarily by economic and transport-activity variables, or whether energy and industrial-structure variables played comparable roles. To answer this question, it estimates road transport CO₂ emissions, builds an indicator system for economic development, industrial structure, energy use, and road transport activity, and uses correlation analysis and PCA to diagnose variable structure before applying LASSO regression to identify variables with stronger explanatory power. The objective is to determine the dominant drivers and effect directions of road transport CO₂ emissions under plateau spatial constraints, thereby clarifying how the emission mechanism in Qinghai differs from that commonly observed in more concentrated plain or urban regions.

2. Literature Review

Research in the academic field on the driving factors of carbon emissions in the transport sector has gradually shifted from a single perspective focused on economic growth to a more comprehensive examination that considers multiple dimensions, including energy, industry, and the economy [4]. A large number of empirical studies have shown that the effects of the economy, industry, and energy on carbon emissions from the transport sector do not exist in isolation, but instead jointly influence the process of transport carbon emissions through complex coupling mechanisms [15]. In the economic dimension, studies usually use per capita GDP and urbanization level to measure regional development, and these factors may further affect transport carbon emissions [14]. This can be attributed to the fact that economic growth tends to concentrate population and

economic activities, which increases demand for passenger travel and freight transport. As transport activities expand, energy consumption also rises, ultimately leading to higher carbon emissions [24–26]. In the industrial dimension, industrial activities and industrial structure change are generally considered to affect resource flows, energy consumption, and transport activities, thereby further influencing carbon emissions [27]. In the energy dimension, research mainly focuses on energy structure and energy efficiency, and typically uses the composition of energy consumption and the intensity of energy use in transport as specific indicators for measurement. Among these, the energy consumption structure reflects the proportion of different types of energy used, while the intensity of energy use in transport is employed to measure the level of energy consumed per unit of output, and together these two aspects jointly determine the overall scale of carbon emissions from the transport sector [28,29]. Overall, existing studies have identified the main influencing factors of carbon emissions in the transport sector from multiple perspectives, and have shown that economic development, industrial activities, and energy use play important roles in the process of forming transport carbon emissions. However, these factors do not operate independently, but instead act together in the process of transport carbon emissions through mutual connections and interactions, which makes the formation mechanism show clear characteristics of complexity.

On this basis, existing studies have further examined the underlying mechanisms and carried out in-depth analyses of the interactions among the economy, industry, and energy. The studies by Fan et al. and Jia et al. show that economic growth is one of the core driving factors of changes in carbon emissions, and Fan et al. show that the degree to which various factors affect carbon emissions differs significantly [30,31]. On this basis, Liu et al. further point out that economic development, industrial structure, and energy use do not act independently, but instead show clear and significant interlinked relationships. Specifically, economic growth and the process of industrialization tend to expand the scale of production, which in turn increases the demand for raw material transportation and product circulation, further drives the growth of transport activities and raises the level of energy consumption, and ultimately leads to an increase in carbon emissions. Meanwhile, higher energy efficiency and a cleaner energy structure can help reduce carbon emissions and weaken the growth trend of emissions. In this process, industrial development influences the level of emissions by changing the way energy is consumed, while economic activities, by promoting industrial expansion and the growth of energy demand, lead the three to form a relationship of mutual interaction and reinforcement [15]. Furthermore, when looking within the transport system itself, this mechanism of influence is usually realized through the process of road transportation. The study by Bo et al., focusing on Tibet as the research area, points out that in high-altitude regions where road transport is the dominant mode, economic growth can increase freight demand and the movement of people, thereby expanding the scale of road transportation and increasing the number of vehicles, which in turn raises energy consumption and directly leads to higher carbon emission. In this process, Hou et al. point out that the way different types of vehicles use energy ultimately determines the final level of emissions. When the number of civilian vehicles reaches a certain scale, low-carbon vehicles, such as hybrid cars and electric vehicles gradually enter the market, thereby reducing the carbon emission intensity per unit of transport activity to some extent. Therefore, even as the total number of vehicles continues to grow, the increase in transport-related carbon emissions may still be moderated under conditions where the energy structure is being improved [8,32]. Overall, carbon emissions in the transport sector can be understood as the outcome of economic development, which drives changes in industrial activities and transport demand, and is ultimately determined by the way energy is used. However, this mechanism

does not manifest in the same way across different regions and stages of development, and the direction and strength of the effects of various factors may change accordingly.

However, most existing studies are based on regions with relatively concentrated spatial layouts and high intensity of land development, or on large metropolitan clusters. In such areas, population and industries are highly concentrated, travel distances are relatively short, and transport demand is more centralized, so the conclusions drawn tend to have relatively strong explanatory power. Building on the studies discussed above, it is possible to raise a further question: within the existing research framework, are the effects of factors such as the economy, industry, and energy on transport-related carbon emissions remain stable? Existing studies generally show that economic growth increases carbon emissions by expanding transport demand, while improvements in the energy structure can help slow this growth trend. However, this mechanism may differ in high-altitude plateau regions. The study by Hong et al. finds that in the southwestern plateau region of China, represented by Yunnan Province, population and industrial activities are spatially dispersed because of terrain and natural conditions, while transport infrastructure remains relatively weak and accessibility in remote areas is relatively low [22]. Under such a spatial structure, basic production and daily living materials often depend on long-distance transportation, which leads to longer transport distances and higher transport frequency, thereby increasing carbon emissions from the transport sector. Similarly, the report of world bank illustrates that in the East African plateau region, using Ethiopia as an example, the road network is unevenly distributed and is constrained by complex terrain and ecological conditions, so both transport infrastructure development and network optimization are restricted, making it difficult to significantly improve transport efficiency through simple expansion of infrastructure [23]. Under such conditions, transport activities show a stronger dependence on long-distance transportation, the impact of economic growth on transport-related carbon emissions may become more direct, and the emission reduction effect of the energy structure in the transport sector remains relatively limited. Therefore, in ecologically fragile plateau regions, whether the relationships among economic, industrial, and energy factors still hold, and whether their impact pathways have changed, still need to be further examined.

In this context, existing studies have begun to pay closer attention to how regional differences influence the driving mechanisms of carbon emissions in the transport sector. The study by Guan and Huang finds that across different regions and at different stages of development, both the direction and the strength of the effects of various factors on transport-related carbon emissions show clear differences, meaning that some factors may play a promoting role in certain regions, while in other regions their effects may weaken or even turn into restraining effects, which indicates that the relationships among variables will adjust as regional conditions change [12]. Sun et al. take Qinghai Province as one of their study areas, and reach a similar conclusion that the dominant factors of transport-related carbon emissions and their relative importance rankings differ across regions [33]. Further studies show that in regions such as Qinghai Province, the relationship between transport-related carbon emissions and economic growth has gradually shown a trend of relative decoupling, and this change is mainly influenced by adjustments in the energy structure, such as the decline in coal consumption and the improvement in the level of renewable energy use. At the same time, the combined influence of factors such as energy efficiency, the level of urbanization, technological investment, and environmental regulation has gradually shifted the formation mechanism of transport-related carbon emissions from a single driving force to a pattern of multi-factor co-evolution, thereby further increasing the complexity of the relationships among the economy, industry, and energy [34,35]. In this context, although existing studies have identified the main influencing factors of transport-related carbon emissions and have revealed their basic mechanisms of

action, the inconsistency of findings across different regions indicates that the effects of these factors are not universally applicable. Particularly in plateau regions, due to differences in natural environmental conditions, levels of economic development, and transport structures, it remains unclear whether the conclusions of existing studies are still applicable, and this lack of clarity has not yet been fully explained. Therefore, it is necessary, within the existing framework of economic, industrial, and energy variables, to further examine whether the roles of these factors still hold in plateau regions, and to identify which factors play a dominant role in such areas.

On this basis, in response to the issues discussed above, relevant research methods have also continued to develop. In existing studies, the modeling approaches for transport-related carbon emissions have evolved from traditional econometric methods toward data-driven approaches, which use machine learning and statistical analysis to establish relationships between carbon emissions and related influencing factors based on data, and are able to capture relatively complex nonlinear characteristics [36]. In traditional approaches, multiple linear regression and decomposition methods are commonly used to analyze the driving factors of carbon emissions. Among them, the STIRPAT model is mainly applied to examine the effects of multiple factors on carbon emissions, while the LMDI method is used to decompose changes in carbon emissions into the contributions of different factors, and these methods have been widely applied in studies on transport-related carbon emissions [15]. Li et al. construct an indicator system based on the STIRPAT model and conduct scenario analysis [16]. Wang et al. combine the decoupling effort model with the LMDI method to identify the extent of the effects of different factors [37]. However, under multivariable conditions, such methods usually require the model form to be specified in advance, which makes it difficult to reflect the complex relationships among variables, and when strong correlations exist among variables, they are also not conducive to identifying the factors that truly play a dominant role. In recent years, some studies have begun to introduce machine learning methods to analyze carbon emissions in the transport sector. Shou et al. use the Random Forest model to screen key influencing factors from multidimensional variables, and combine it with the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method to reveal the causal relationships among factors and their interaction network, thereby identifying the key driving factors of transport-related carbon emissions and their spatial heterogeneity [38]. Li et al. integrate XGBoost and GTWR into a GTBoost model to explain the spatiotemporal heterogeneity of the built environment's effects on transport-related carbon emissions and to capture their nonlinear relationships [39]. Wu et al., building on the LMDI decomposition approach, combine a Back Propagation (BP) neural network with scenario analysis to model and predict carbon emissions [40]. Although the methods mentioned above have certain advantages in capturing complex relationships and improving prediction accuracy, their research focus is mostly on carbon emission prediction or indirect analysis across multiple regions, and their support for variable selection and the interpretation of results remains relatively limited. Particularly in situations with many variables and strong correlations among them, how to identify the key factors that play a dominant role in transport-related carbon emissions from a large number of indicators remains an issue that still needs to be addressed. In this context, there is a need for a method that can simultaneously handle correlations among variables and carry out variable selection. By contrast, LASSO regression introduces a penalty term during the model estimation process, which allows it to automatically select a small number of key variables under multivariable conditions and effectively mitigate the problem of correlations among variables, thereby improving the stability and interpretability of the model results. The study by Tang et al. shows that the LASSO method can extract key variables from a multidimensional indicator system and enhance the explanatory power of the model [19]. Therefore, this study applies the LASSO

regression method to screen the influencing factors of transport-related carbon emissions, and on this basis further analyzes the mechanisms through which the key variables exert their effects.

3. Materials and Methods

3.1. Study Area

Qinghai Province is situated in the northeastern Qinghai–Tibetan Plateau, with an average elevation exceeding 3000 m and a total area of approximately 720,000 km² [41]. High-altitude ecological elements such as glaciers and permafrost are widely distributed across the region [42]. Its ecosystem is relatively fragile and highly sensitive to climate change and human activities, resulting in greater ecological and environmental pressure under the similar level of carbon emissions [43,44]. In addition, high altitude, complex terrain, and land development constraints pose challenges to transport infrastructure construction, making regional development highly dependent on long-distance road transport [45]. Moreover, Qinghai Province is characterized by resource extraction and primary processing industries. In recent years, the province has actively promoted the “One High and Four Bases” development strategy, under which ecological tourism, green agricultural and livestock products, and clean energy industries have continued to expand, generating significant demand for regional transport activities [46–50]. The main regional characteristics of Qinghai Province related to transport carbon emissions are summarized in Table 1.

Table 1. Key Regional Characteristics of Qinghai Province Relevant to Transport Carbon Emissions.

Category	Main Characteristics
Geographic Location	Northeastern Qinghai–Tibetan Plateau
Average Elevation	Above 3000 m
Land Area	Approximately 720,000 km ²
Ecological Environment	Widespread distribution of glaciers and permafrost fragile ecological environment
Ecological Characteristics	Highly sensitive to climate change and human activities
Land Development Conditions	Limited developable land resources
Transport Conditions	High altitude and complex terrain increase the difficulty of transport infrastructure construction
Transport Characteristics	Strong dependence on long-distance road transport
Transport Infrastructure	Relatively underdeveloped transport infrastructure in rural and pastoral areas
Industrial Structure	Dominated by resource extraction and primary processing industries
Representative Industries	Salt lake chemical industry, electric power industry, etc.
Regional Strategy	“One High and Four Bases” development strategy
Tourism and Logistics	Growing demand for ecological tourism and agricultural/livestock product transportation
Clean Energy	Abundant hydropower, solar, and wind energy resources

Overall, Qinghai Province shares many typical features of high-altitude and ecologically fragile regions, including high environmental sensitivity, a distinctive industrial structure, strong dependence on transport activities, rich clean energy resources, and active policy support. Therefore, using Qinghai Province as a case study can help reveal the characteristics and driving factors of road transport carbon emissions in high-altitude

regions, while also providing useful insights for other ecologically fragile areas with similar conditions. The study area is shown in Figure 1.



Figure 1. Study area of Qinghai Province in China, including the regional road network and major administrative divisions.

3.2. Measurement of CO₂ Emissions

In the accounting system for carbon dioxide emissions, there are generally two main approaches: one is based on the guidelines provided by the Intergovernmental Panel on Climate Change (IPCC), which estimates emissions by converting energy consumption data, and this approach has been widely used due to its high data availability and relatively low difficulty in data collection. The second approach is based on the detailed calculation of actual energy consumption during the operation of different transport modes, but its practical application is constrained to some extent by the lack of relevant monitoring data and inconsistencies in statistical quality [15,51,52]. Taking into account both the availability and the reliability of data, this study adopts the first accounting approach, and the specific calculation model is presented in Equation (1):

$$C_1 = \sum_{i=0}^n E_i \cdot e_i \cdot K_i \cdot \frac{44}{12} \quad (1)$$

In Equation (1), C_1 denotes CO₂ emissions from fossil-energy consumption, i denotes the energy type, E_i denotes the reported consumption of energy type i , e_i is the standard coal conversion coefficient used to convert physical energy consumption into standard coal, and K_i is the carbon-content coefficient per unit of standard coal equivalent. The factor $44/12$ converts carbon into carbon dioxide.

The standard coal conversion factors and carbon emission factors for different energy types were derived from the *IPCC Guidelines for National Greenhouse Gas Inventories* and the *China Energy Statistical Yearbook*. The corresponding parameters are listed in Table 2. All parameters presented in Table 2 are original coefficient values obtained from official statistical sources and the IPCC guidelines. These coefficients were used directly in the carbon emission calculations without any standardization, normalization, or other data transformation procedures. Since the energy consumption data used in this study were already reported in standard coal equivalent terms, the carbon emission calculations were conducted using the carbon emission factor corresponding to standard coal. This

approach ensures the comparability of results across different years and energy types and avoids inconsistencies in coefficient application caused by repeated conversions.

Table 2. Summary of carbon emission calculation parameters.

ith Fuel	Coal	Coke	Crude Oil	Gasoline	Kerosene	Diesel Fuel	Fuel Oil	Natural Gas
e_i	0.7143	0.9714	1.4286	1.4714	1.4714	1.4571	1.4286	1.33
K_i	0.7559	0.855	0.5857	0.5538	0.5714	0.5921	0.6185	0.4483

Note: The upper row reports standard coal conversion coefficients, and the lower row reports carbon-content coefficients for different energy types.

3.3. Construction of Measurement Indicators for Transport Carbon Emission

Based on the studies discussed above, this paper constructs an indicator system from four dimensions: economic development, industrial structure, energy factors, and transport sector. In the process of selecting indicators, this study draws on commonly used variables in existing research and, at the same time, takes into account the characteristics of Qinghai Province, such as its high-altitude setting, strong dependence on transport, a relatively high share of resource-based industries, and clear differences in its energy structure, in order to screen and integrate the indicators and build a multidimensional analytical framework that can reflect regional development features. This study mainly focuses on the impacts of economic development, industrial structure, energy-related industries, and road transport activities on road transport carbon emissions. It should be noted that the development of new energy vehicles, railway transport, and clean energy utilization may also contribute to changes in transport carbon emissions. In particular, continuous statistical data on new energy vehicle-related indicators are unavailable for the study period, which limits their suitability for long-term analysis. Although railway transport development may influence road transport carbon emissions through modal substitution effects, it falls outside the scope of this study, which focuses on the internal driving mechanisms of the road transport system. Furthermore, clean energy development may affect transport carbon emissions indirectly through changes in the energy structure, and the associated mechanisms are relatively complex. Therefore, these factors were not incorporated into the analytical framework of this study. Future studies may investigate their impacts using more comprehensive and consistent datasets.

In the economic dimension, this study selects indicators including Gross Domestic Product (GDP), per capita Gross Domestic Product (PGDP), the share of the primary industry (SPIG), the share of the secondary industry (SSIG), the share of the tertiary industry (STIG), the GDP index (GDPI), the per capita GDP index (PGDPI), and the value added of the transportation, storage, and postal sector (VATSP). These indicators jointly describe the level of regional economic development from multiple aspects, including economic scale, development level, industrial base, and transport-related service activities, and are used to reflect how economic growth, by expanding production and consumption activities and increasing the demand for population mobility and goods circulation, further influences the scale of transport and the level of carbon emissions.

In the dimension of industrial structure, this study selects indicators such as the proportion of coal mining and washing industry (CWI), the share of non-ferrous metal mining and dressing industry (NMI), the share of petroleum and natural gas extraction industry (PNG), the total output value of the new energy industry (NEI), the total output value of the new materials industry (NMO), the total industrial output value of petroleum and natural gas extraction (PNGO), the total industrial output value of the electric power industry (EPO), the total output value of the salt lake chemical industry (SLC), and the total output value of the non-ferrous metal industry (NFMO). These indicators make it possible to analyze the differences in how various types of industries contribute to the formation

of transport demand, and to examine how changes in industrial structure influence the pathways of transport-related carbon emissions.

In the energy dimension, this study selects indicators such as the share of energy consumption in the coal mining and washing industry (CWE), the share of energy consumption in the petroleum and natural gas extraction industry (PNGEC), the share of energy consumption in the ferrous metal mining industry (FMEC), and the share of terminal energy consumption in the non-ferrous metal mining industry (NMEC). These indicators are mainly used to describe the structure of energy consumption and the energy use characteristics of different energy-related industries, and to focus on examining, under the background of continuous adjustments in the energy structure, whether different patterns of energy use still have a significant impact on transport-related carbon emissions, and whether this impact is reflected directly or realized indirectly through other factors.

In the transport dimension, this study selects indicators including highway passenger volume (HPT), highway freight volume (HFT), highway freight turnover (THFT), civilian vehicle ownership (CVO), highway mileage (HM), and total passenger turnover (TPT). These indicators directly reflect the scale of road transport, the intensity of transport activities, and the level of vehicle use, and can more clearly show how changes in the scale of transport activities affect carbon emissions.

Overall, the indicator system constructed in this study does not focus on analyzing a single variable, but instead introduces multidimensional indicators in a comprehensive manner to identify, in the subsequent model, the direction of influence and the relative importance of different factors on transport-related carbon emissions, thereby clarifying which factors still have significant effects, which have relatively weakened impacts, and which have become key driving factors under plateau conditions. Table 3 provides a detailed list of the specific indicators under each dimension and summarizes their classification, units, and corresponding codes.

Table 3. Indicator System of Driving Factors of Transport-Related Carbon Emissions in Qinghai Province.

Dimension	Indicator Name	Unit	Code
Economy	GDP	100 million	X1
	PGDP	100 million	X2
	SPIG	%	X3
	SSIG	%	X4
	STIG	%	X5
	GDPI	100 million	X6
	PGDPI	100 million	X7
	VATSP	100 million	X8
Industry	CWI	%	X9
	NMI	%	X10
	PNG	%	X11
	NEI	100 million	X12
	NMO	100 million	X13
	PNGO	100 million	X14
	EPO	100 million	X15
	SLC	100 million	X16
	NFMO	100 million	X17
Energy	CWEC	%	X18
	PNGEC	%	X19
	FMEC	%	X20
	NMEC	%	X21

Road Transport	HPT	10,000 persons	X22
	HFT	10,000 tons	X23
	THFT	10,000 ton-kilometers	X24
	CVO	unit	X25
	HM	km	X26
	TPT	10,000 passenger-kilometers	X27

Monetary variables are measured in 100 million yuan; percentage indicators are expressed as (%); transport variables are measured in persons, tons, vehicles, kilometers and passenger-kilometers (all in ten-thousand units). Data are from the Qinghai Statistical Yearbook and China Energy Statistical Yearbook.

3.4. Influencing Factor Identification Method

To identify key variables with strong explanatory power for transport-related carbon emissions, this study applies the LASSO regression method to screen the initially selected indicators. LASSO regression introduces an L1 regularization penalty into the traditional linear regression model. By imposing constraints on the regression coefficients, it allows some coefficients to shrink gradually to zero during estimation, thereby removing variables with weaker effects and retaining indicators with stronger explanatory power. This method is well suited to situations with many explanatory variables and correlations among them, as it can simplify the model structure, alleviate multicollinearity to some extent, and reduce the risk of overfitting. Therefore, this study applies LASSO regression to screen the influencing factors of transport-related carbon emissions, and its objective function can be expressed as follows:

$$T = \min\{\|X_w - y\|_2^2 + \lambda\|w\|_1\} \quad (2)$$

X represents the matrix of explanatory variables, y is transport-related carbon emissions, w is the vector of regression coefficients, and λ is the regularization parameter used to control the degree of coefficient shrinkage. When λ takes a larger value, the coefficients of more variables are shrunk to zero, thereby achieving stronger variable selection. When λ is smaller, the model becomes closer to ordinary least squares regression.

Correlation analysis and Principal Component Analysis (PCA) are used before LASSO to examine the variable structure and diagnose multicollinearity. PCA transforms a set of correlated variables into a smaller number of orthogonal principal components and shows how much information can be retained by these components. In this study, PCA is not used to replace the original indicators in the final driver interpretation. Instead, it provides evidence of information overlap among indicators and justifies the use of LASSO for variable selection under multicollinearity.

In addition, because this study is based on annual time-series data from 2003 to 2022, some economic, industrial, energy, and transport-related variables may contain long-term trends and non-stationary characteristics. If non-stationary time-series data are directly used for regression analysis, spurious regression problems may occur, which could affect the reliability of the variable selection results. Therefore, the Augmented Dickey–Fuller (ADF) unit root test was conducted on road transport CO₂ emissions and the key variables selected by the LASSO model to examine their stationarity. The test helps determine whether the variables contain unit roots and provides a statistical basis for interpreting the subsequent model results.

Based on the stationarity test results, the Engle–Granger cointegration test was further conducted to examine whether a long-term equilibrium relationship exists between road transport CO₂ emissions and the key influencing factors. The cointegration test can determine whether a stable long-term relationship exists among non-stationary variables, thereby reducing the risk of spurious regression that may arise from the direct analysis of

non-stationary time-series data. If a cointegration relationship exists among the variables, it indicates that although they may fluctuate in the short term, they still maintain a relatively stable equilibrium relationship in the long term. Therefore, the ADF unit root test and the Engle–Granger cointegration test were jointly employed to improve the reliability of the variable selection results and the interpretation of long-term driving mechanisms. All statistical analyses and figure generation were performed using Python (version 3.14).

3.5. Data Sources

This study uses annual data for Qinghai Province from 2003 to 2022 to estimate road transport CO₂ emissions and identify their driving factors. Data on energy consumption in the transport sector, as well as the conversion coefficients used to convert physical energy quantities into standard coal units, are obtained from the 2004 to 2023 *Qinghai Statistical Yearbook* published on the official website of the Qinghai Provincial Bureau of Statistics. Carbon emission factors are derived from the IPCC Guidelines for National Greenhouse Gas Inventories. Economic indicators, industrial-structure indicators, energy-related indicators, and transport-related data, including passenger and freight volumes and turnover, are also obtained from the 2004 to 2023 *Qinghai Statistical Yearbook*.

Among the indicators selected in this study, only the total output value of the new energy industry (NEI) and the total output value of the new materials industry (NMO) lack official statistical data for the period 2003–2010, while the time-series data for all other indicators are relatively complete. This is mainly because the new energy and new materials industries in Qinghai Province were still at an early stage of development during 2003–2010. The number of related enterprises and the scale of these industries were relatively small and had not yet been included as independent statistical categories in the *Qinghai Statistical Yearbook*. Therefore, no continuous official statistical records were available before 2011. As these industries gradually expanded and reached a sufficient scale, the corresponding indicators were separately recorded and continuously reported in the statistical yearbooks. To address this issue, linear interpolation was applied to the missing observations to preserve the continuity of the time series. Since the missing data involve only two variables and mainly result from statistical classification limitations rather than random omissions, and because this study focuses on identifying long-term driving mechanisms rather than short-term prediction, the impact of this treatment on the overall LASSO results is expected to be limited.

It should be noted that although more recent editions of the *Qinghai Statistical Yearbook* have been published, some indicators have been merged, adjusted, or further disaggregated since the 2024 edition (corresponding to 2023 data). As a result, the statistical definitions of certain indicators are not fully consistent with those used in earlier years, which may affect the comparability of long-term time-series data. To ensure the consistency of the dataset and the reliability of the analytical results, this study employs only data based on a consistent statistical scope and definition throughout the period 2003–2022. Furthermore, the primary objective of this study is to identify the long-term drivers of road transport carbon emissions rather than to capture short-term variations. Therefore, the omission of data from the most recent two years is not expected to materially affect the main findings of the study.

4. Results

4.1. Characteristics of Transport Carbon Emission Changes and Correlation Analysis of Variables

Before identifying the influencing factors of transport carbon emissions, it is first necessary to analyze the relationships among variables and the overall structure of the variable system. Figure 2 shows the correlations between transport carbon emissions and different variables, as well as the correlations among the variables themselves. The results indicate that variables related to economic development and transport activities generally show strong positive correlations. Among them, the GDP index (GDPI), value added of transportation, storage and postal services (VATSP), civil vehicle ownership (CVO), and passenger turnover (TPT) all show strong positive correlations with transport carbon emissions, indicating a clear relationship between economic growth, the expansion of transport activities, and the increase in transport carbon emissions. At the same time, strong correlations also exist among some variables. For example, GDPI shows high correlation coefficients with both VATSP and CVO. This indicates that there are clear interactions among economic development, transport activities, and vehicle scale, and there may be some overlap in the information reflected by different variables. If all variables are directly included in a traditional regression model, the results may be affected by multicollinearity, which could reduce the stability of the model results.

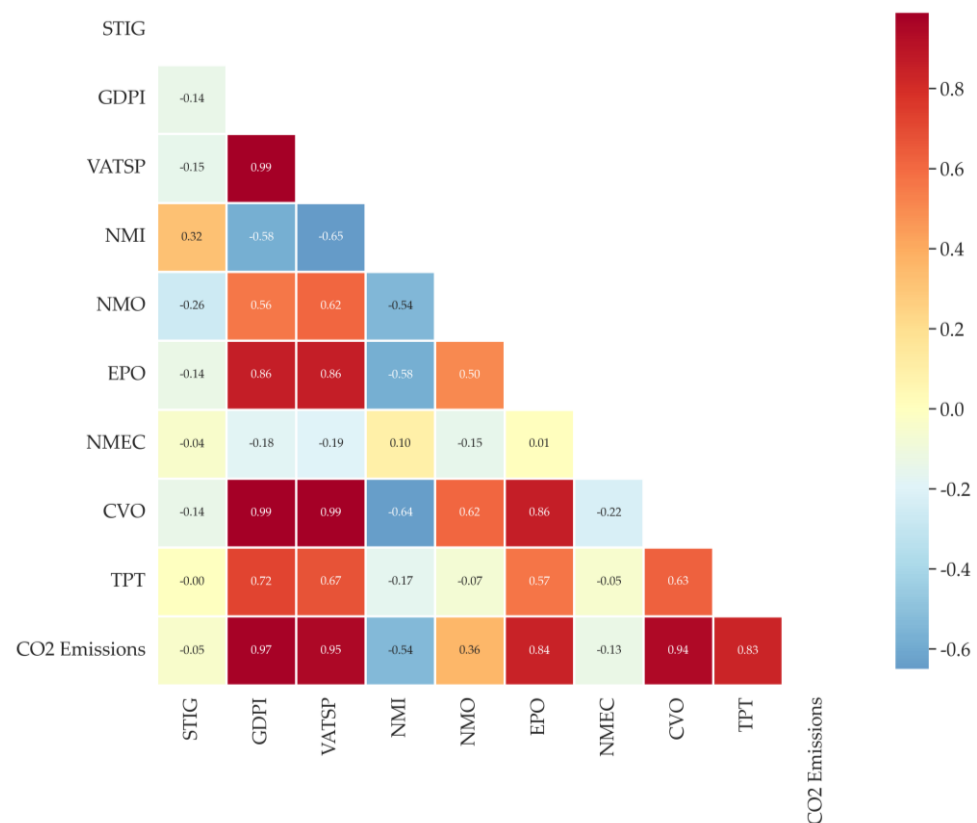


Figure 2. Correlation matrix of key indicators.

To further analyze the overall structural characteristics among the variables, principal component analysis (PCA) was conducted in this study, and the results are shown in Figure 3. The results show that the first principal component can already explain a large proportion of the original information. As the number of principal components increases, the cumulative variance contribution rate rises rapidly. The first three principal

components are able to explain most of the variable information, while the additional information provided by the remaining principal components is relatively limited. This result indicates that there is obvious information overlap and correlation within the current variable system, and the variables are not completely independent from each other. Therefore, if ordinary regression methods are directly used for analysis, the results may be affected by multicollinearity. Based on these results, it is necessary to further identify the key influencing factors of transport carbon emissions by using a variable selection method that can handle correlations among variables.

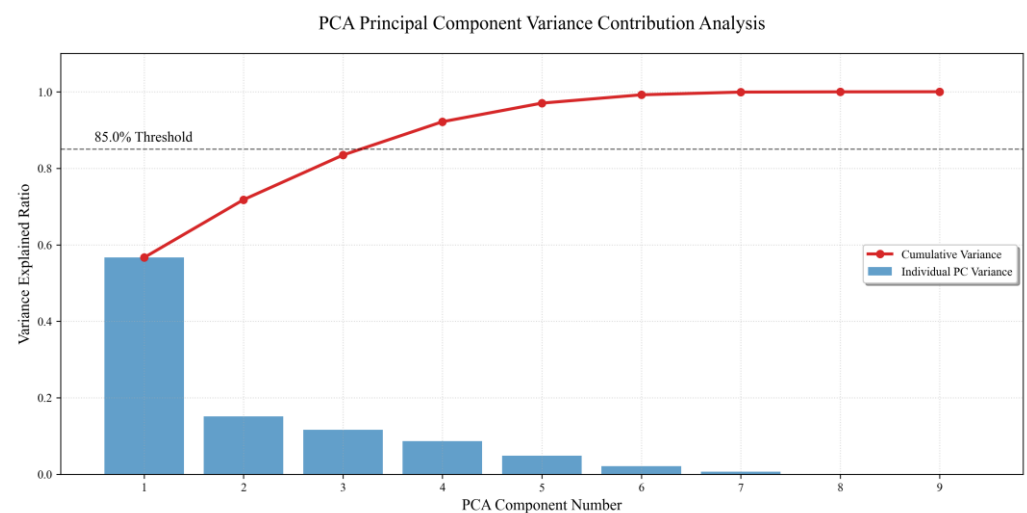


Figure 3. PCA principal component variance contribution analysis.

4.2. Identification of Key Influencing Factors Based on LASSO Regression

Based on the results of the correlation analysis and principal component analysis above, there are strong correlations and information overlap within the current variable system. Therefore, this study further applies the LASSO regression model for variable selection to identify the core factors that have key influences on transport carbon emissions.

4.2.1. Parameter Determination of the LASSO Regression Model

To determine the penalty parameter in the LASSO regression, this study uses a cross-validation approach to compare the model performance under different parameter settings, and on this basis selects the parameter to be used in the subsequent analysis. In Figure 4, the two vertical dashed lines correspond to different parameter selection criteria. The blue dashed line represents the parameter associated with the minimum error (Min-MSE Alpha), at which point the model shows a better fitting performance, but a relatively larger number of variables are retained. The black dashed line represents a more parsimonious model obtained when the change in error is not significant (Parsimonious Alpha), and this model contains a smaller number of variables. Considering that the main purpose of this study is to analyze the underlying mechanisms rather than to construct the simplest possible model, the parameter corresponding to Min-MSE Alpha is selected in the subsequent analysis, so as to retain more variables with explanatory value.

As shown in Figure 4, as the penalty parameter gradually increases, the model error shows clear stage-wise changes. In the left region, the error value is relatively high and decreases rapidly, which indicates that when the penalty is weak, the model includes a larger number of variables, the structure is more complex, and the correlations among variables are relatively strong, leading to a poorer fitting performance for carbon emission changes. However, as the penalty strength increases, the error decreases rapidly and reaches its lowest value when it approaches the blue dashed line at Min-MSE Alpha,

which indicates that the model achieves the best fit to the changing trend of transport-related carbon emissions at this point. After the blue dashed line, as the penalty continues to increase, the change in error becomes much smaller, the overall trend becomes more stable, and the error shows a slight increase. This indicates that some variables have been gradually shrunk or even removed, and the model begins to lose part of the information, so its ability to explain changes in carbon emissions no longer continues to improve. The black dashed line corresponds to the parsimonious parameter (Parsimonious Alpha). Although the error does not increase significantly, the penalty is stronger, fewer variables are retained, and the model becomes simpler. For studies that focus on prediction, choosing the parameter corresponding to the black dashed line is reasonable, because it places more emphasis on model simplicity and stability, but the focus of this study is to identify the key influencing factors of transport-related carbon emissions and to analyze the relationships among variables, so it is necessary to retain as many variables with explanatory value as possible. Based on this research purpose, this study ultimately selects the parameter corresponding to the blue dashed line, Min-MSE Alpha, and treats the result corresponding to the black dashed line, Parsimonious Alpha, as a reference, which is used to help assess whether the variable selection results are stable.

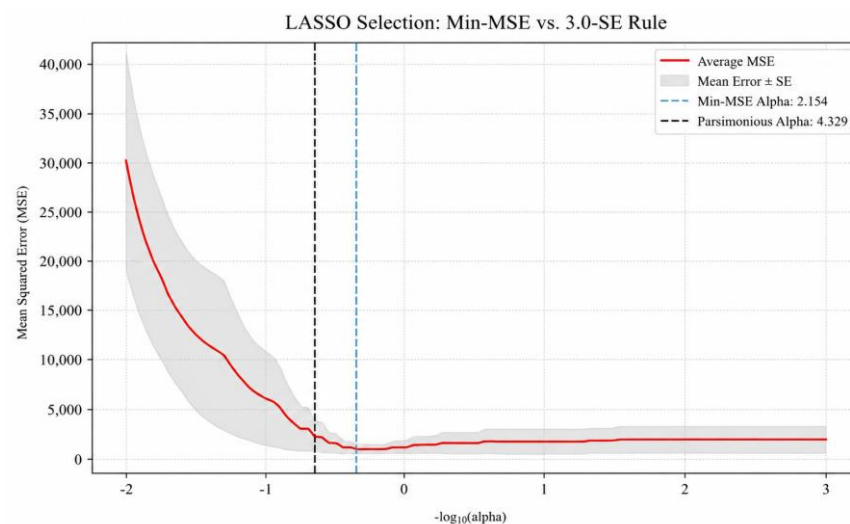


Figure 4. Cross-Validation Curve for LASSO Parameter Selection.

4.2.2. Explanation of the Variable Selection Process in the LASSO Regression Model

After determining the penalty parameter through cross-validation, it is still necessary to further analyze how variables are selected under this parameter setting. Cross-validation can only indicate which parameter is more appropriate, but it cannot show how each variable changes during the selection process. Therefore, a LASSO coefficient path plot is introduced to observe how the coefficients of each variable gradually shrink as the penalty strength increases, and to identify which variables are ultimately retained, thereby providing a basis for identifying the key influencing factors.

As shown in Figure 5, the horizontal axis of the path plot is $-\log_{10}(\alpha)$, and moving from right to left means that the penalty gradually becomes stronger. When the penalty is weak, the coefficients of most variables are relatively large, and the model includes a larger number of variables. As the penalty becomes stronger, the coefficients of the variables gradually shrink toward zero, and some variables are compressed to zero and are removed from the model. At the position of the blue dashed line corresponding to Min-MSE Alpha, many coefficient paths still remain non-zero, which indicates that the model retains a relatively large number of variables. In contrast, at the position of the black

dashed line corresponding to Parsimonious Alpha, more variables shrink to zero, and the model structure becomes more simplified. Overall, as the penalty parameter changes, different variables show different behaviors during the selection process, with some variables shrinking to zero quickly, while others remain non-zero over a relatively wide range. Under the selected parameter setting, the variables that remain non-zero can be regarded as having relatively strong explanatory power for transport-related carbon emissions. Therefore, by combining the results of the coefficient path plot and cross-validation, through LASSO selection, key variables with strong explanatory power for transport carbon emissions can be retained while reducing variable redundancy and the influence of multicollinearity.

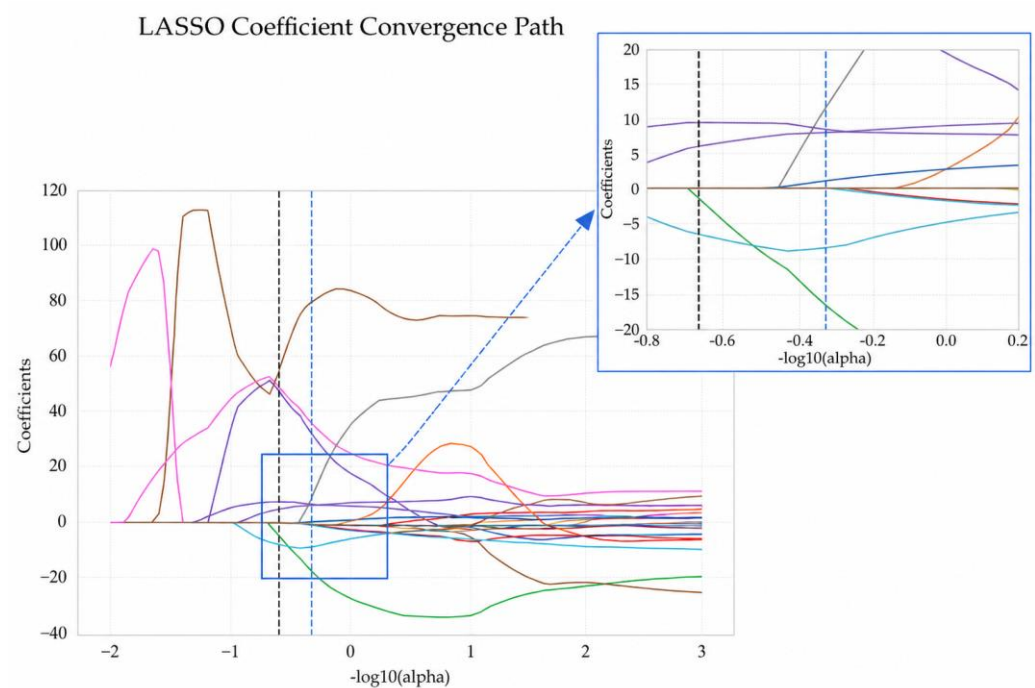


Figure 5. LASSO Coefficient Path of Explanatory Variables.

4.2.3. Variable Selection in the LASSO Regression Model

To further verify the LASSO selection results and analyze the dynamic relationships between key variables and transport carbon emissions, this study further analyzes the co-evolution trends between different variables and transport carbon emissions, and the results are shown in Figures 6 and 7.

Among them, the GDP index (GDPI), value added of transportation, storage and postal services (VATSP), civil vehicle ownership (CVO), and passenger turnover (TPT) all show stable positive effects on transport carbon emissions. This indicates that economic growth and the expansion of transport activities remain the core driving forces behind the increase in transport carbon emissions in Qinghai Province. Figure 7a further shows that the overall changing trends of GDPI and VATSP are generally consistent with those of transport carbon emissions. Especially after 2006, the growth slope of transport carbon emissions increased significantly and showed a continuous upward trend overall. This indicates that as regional economic activities gradually increased, infrastructure construction, material circulation, and transport demand expanded simultaneously, which further promoted the growth of transport energy consumption and carbon emissions. Among these variables, GDPI shows the most significant effect, indicating that economic growth remains an important factor driving the increase in transport carbon emissions.

In the transport dimension, CVO and TPT also show significant positive effects on transport carbon emissions. Figure 7d shows that both variables present a continuous upward trend and are highly consistent with the changes in transport carbon emissions. Among them, the increase in civil vehicle ownership means that road transport activities become more frequent, while fuel consumption also further increases. The growth of passenger turnover reflects the increase in residents' travel demand and regional mobility. Especially under the background of tourism development and the continuous strengthening of regional transport connections, the growth of passenger transport activities further increases the level of transport energy consumption. This further indicates that the expansion of transport activities remains an important factor driving the growth of transport carbon emissions.

In contrast, variables related to industry and energy show more complex relationships with transport carbon emissions. Among them, the proportion of the non-ferrous metal mining and dressing industry (NMI) and the total output value of the new materials industry (NMO) both show negative effects, indicating that some industrial structure adjustments may help reduce transport carbon emissions. Figure 7c further shows that the total output value of the new materials industry (NMO) generally presents an opposite changing trend to transport carbon emissions. This may indicate that as some industries gradually develop toward higher technological levels and higher transport efficiency, the transport intensity per unit of output decreases, thereby reducing the growth of transport carbon emissions to some extent. At the same time, there are also differences among different indicators within the same industry. For example, the share of the non-ferrous metal mining and dressing industry (NMI) shows a negative effect, while the share of terminal energy consumption of the non-ferrous metal mining and dressing industry (NMEC) shows a weak positive effect. Figure 6 shows that NMEC has relatively large fluctuations overall, indicating that the influence of changes in industrial energy use patterns on transport carbon emissions is not stable at different stages, and its effect has certain stage characteristics. This indicates that the industrial structure itself and industrial energy use patterns may affect transport carbon emissions through different pathways.

Notably, Figure 7a,b show that road transport carbon emissions increased more rapidly after 2006, while GDPI and VATSP exhibited trends that were highly consistent with this change. This period coincided with the rapid development of resource-based industries in Qinghai Province. The expansion of the nonferrous metal industry and the development of the Qaidam Circular Economy Pilot Zone promoted economic growth, infrastructure construction, and transport demand, leading to higher transport energy consumption and carbon emissions [53]. Meanwhile, NMEC showed a clear peak around 2008–2009, possibly due to the rapid expansion of the nonferrous metal mining industry. This reflects the short-term effects of resource development on energy consumption and transport carbon emissions.

Overall, the dynamic changing trends shown in Figure 7 are generally consistent with the LASSO variable selection results. Economic and transport-related variables show strong synchronous relationships with transport carbon emissions, while industrial and energy variables show more fluctuating and indirect effects. This further verifies the reliability of the LASSO selection results and also indicates that there are clear differences in the mechanisms through which variables from different dimensions affect transport carbon emissions.

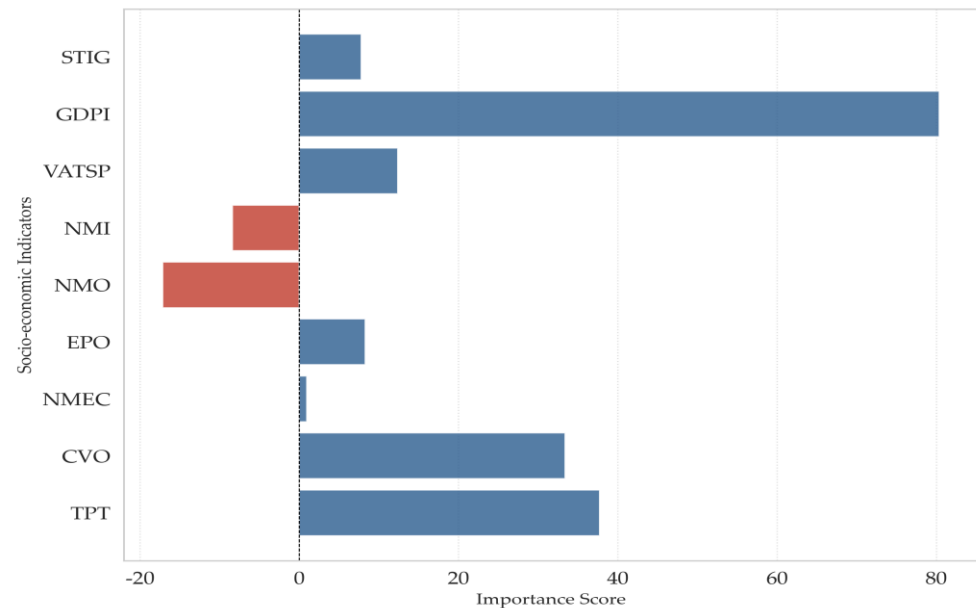


Figure 6. Feature selection results based on LASSO regression.

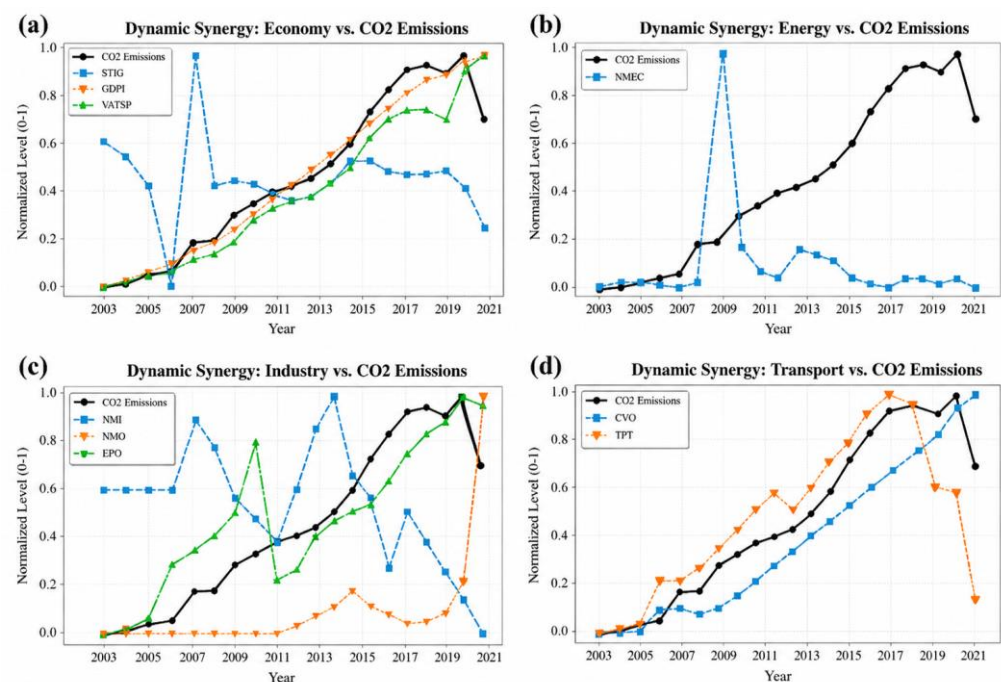


Figure 7. Dynamic Synergy between CO₂ Emissions and Key Driving Factors.

4.2.4. Model Fitting Performance of the LASSO Regression

To further examine the overall fitting performance of the LASSO model, this study compares the fitted values of the LASSO model with the actual transport carbon emissions. The results are shown in Figure 8. It can be seen that most sample points are distributed near the ideal fitting line, indicating a high consistency between the fitted results of the LASSO model and the actual values. At different emission levels, the model can stably reflect the changing trend of transport carbon emissions, and no obvious systematic deviation is observed. This result indicates that the LASSO model can not only effectively handle the correlation problem among variables, but also stably reflect the changing characteristics of transport carbon emissions, providing a basis for the subsequent mechanism analysis and robustness tests.

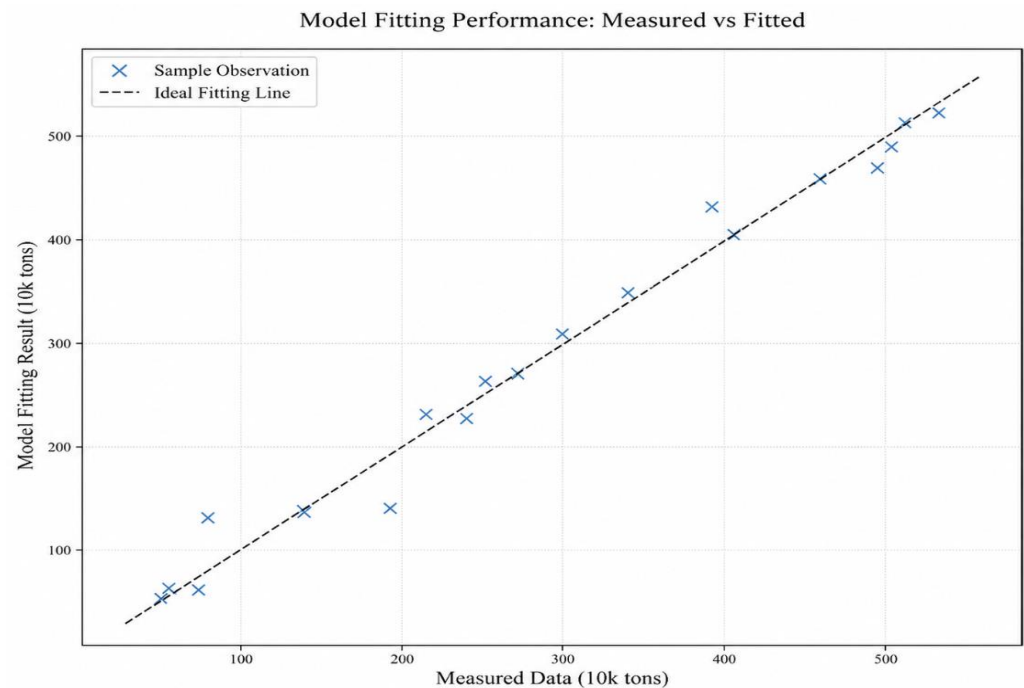


Figure 8. Comparison between measured and model-fitted CO₂ emission.

4.3. Robustness Test

4.3.1. Multi-Model Comparison

To examine whether the fitted emission trend is model-dependent, this study further constructs multiple models under the same variable system, including support vector regression (SVR), random forest (RF), gradient boosting machine (GBM), extreme gradient boosting (XGBoost), and BP neural network models, and compares the fitting results of different models. Since the focus of this study is to identify the key influencing factors of transport carbon emissions rather than to conduct long-term prediction, this section uses model comparison as a robustness and supplementary fit check for the changing trends of transport carbon emissions.

Figure 9 shows the overall relationships between the fitting results of different models and the actual transport carbon emissions. The results indicate that all models can generally reflect the changing trends of transport carbon emissions well, and the fitting curves are generally consistent with the changing direction of the actual values. Among them, the overall fitting results of the LASSO, RF, GBM, and XGBoost models are relatively close to the actual values and can stably follow the changing trends of transport carbon emissions. In contrast, the SVR and BP models show relatively large fluctuations in some years, and their fitting stability is relatively weaker. Furthermore, Figure 10 shows the individual fitting results of each model. From some specific years, there are still certain differences among the models. Among them, the BP model shows relatively obvious fluctuations during 2007–2012, and large deviations appear in some years. The SVR model shows a more obvious deviation from the actual values in the later stage, indicating that its ability to stably capture the changing trends of transport carbon emissions is relatively limited under the current sample conditions. In contrast, the RF, GBM, and XGBoost models show relatively stable overall performance, although certain errors still exist in some years. In contrast, the overall fitting results of the LASSO model maintain high consistency with the actual values, and no obvious abnormal fluctuations are observed at different stages. At the same time, the LASSO model can not only stably reflect the overall changing trends of transport carbon emissions, but also effectively reduce variable redundancy and the influence of multicollinearity during the variable selection process. Therefore, compared

with models that mainly focus on fitting performance, LASSO is more consistent with the research objective of identifying key influencing factors in this study.

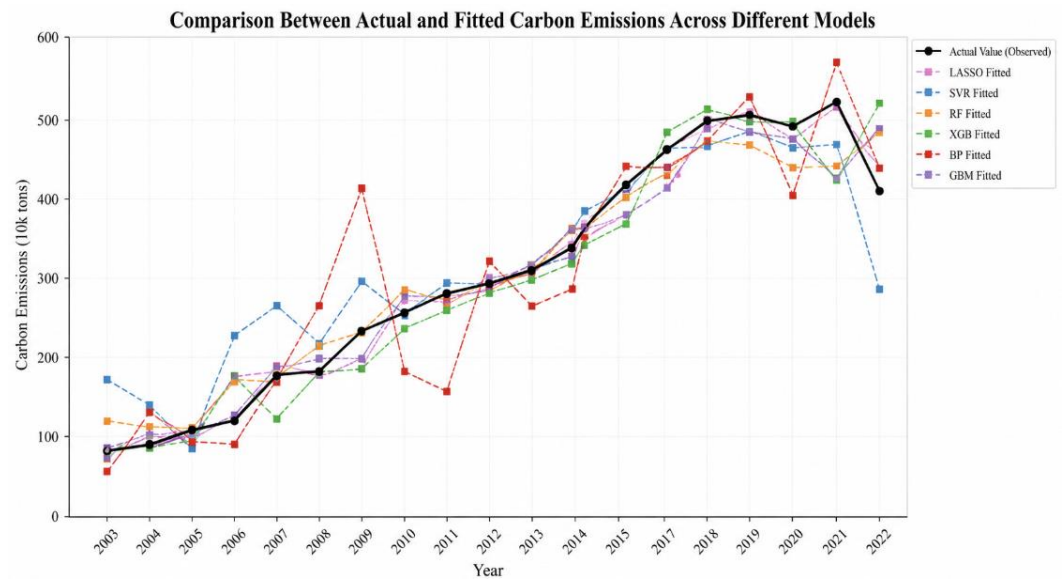


Figure 9. Comparison Between Actual and Fitted Carbon Emission Across Different Models.

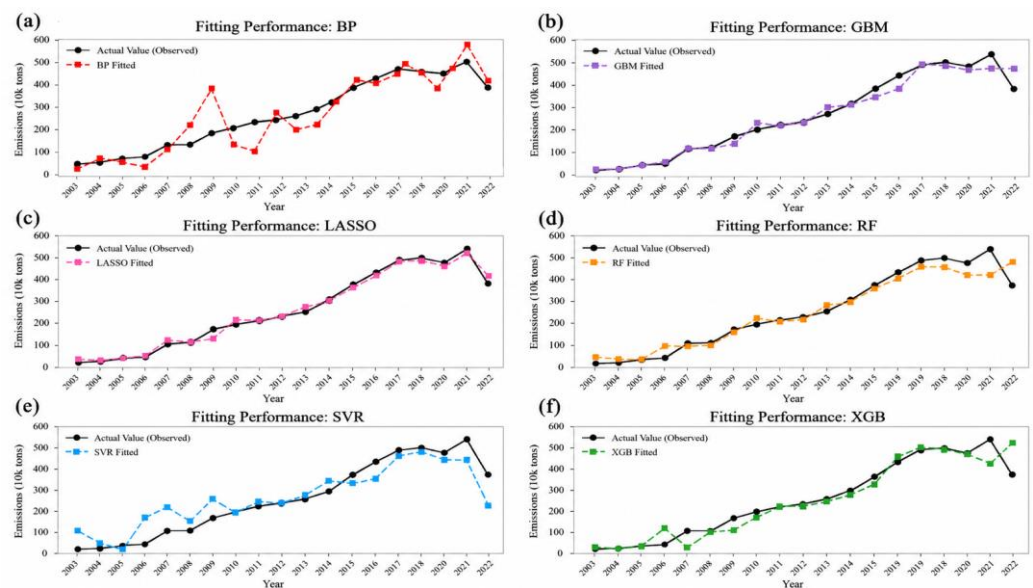


Figure 10. Fitting Performance of Individual Models for Carbon Emissions.

To further quantitatively compare the fitting performance of different models, this study further calculated the mean squared error (MSE), mean absolute error (MAE), and coefficient of determination. The results are shown in Table 4. The results indicate that the LASSO model shows the best performance across multiple indicators (R^2). Among them, the MSE and MAE values of the LASSO model are 434.40 and 14.19, respectively, and the R^2 value reaches 0.983, indicating that the model can effectively reflect the overall changing trends of transport carbon emissions while maintaining relatively low error levels. In contrast, although the RF and GBM models also have relatively high R^2 values, their error levels are clearly higher than those of the LASSO model. Among them, the MSE values of the RF and GBM models are 1668.07 and 1733.17, respectively, both of which are significantly higher than that of the LASSO model. The overall performance of the XGBoost model is between that of the RF and SVR models. Although it can relatively well follow the changing trends of transport carbon emissions, its error level is still relatively high. At

the same time, the overall fitting stability of the SVR and BP models is relatively weak. Among them, the MSE value of the SVR model reaches 3418.28, while that of the BP model further increases to 5656.14. Meanwhile, the R^2 values of both models are also clearly lower than that of the LASSO model. This indicates that under the current variable system and small-sample conditions, the SVR and BP models are more likely to show large fluctuations or obvious fitting deviations in some years.

Table 4. Qualitative Comparison of Model Fitting Performance.

Model	MSE	MAE	R^2
LASSO	434.40	14.19	0.983
RF	1668.07	30.28	0.935
GBM	1733.17	27.52	0.933
XGBOOST	2698.14	36.74	0.896
SVR	3418.28	41.71	0.868
BP	5656.14	57.10	0.781

Lower MSE and MAE values indicate better fitting performance, while a higher R^2 value indicates stronger explanatory ability of the model.

4.3.2. ADF and Cointegration Tests

Although the multi-model comparison further demonstrated the robustness of the LASSO results, some variables related to economic development, industrial structure, and transport activities may contain long-term trends due to the use of annual data from 2003 to 2022, which may lead to non-stationary time-series characteristics. To further verify the reliability of the variable selection results and reduce the risk of spurious regression, the Augmented Dickey–Fuller (ADF) unit root test was applied to road transport carbon emissions and the key variables identified by the LASSO model. The results are shown in Table 5.

The ADF test results (Table 5) show that most economic, industrial, and transport-related variables exhibit non-stationary characteristics at the level form, reflecting clear long-term trends. This is consistent with the long-term changes associated with regional economic growth, transport activity expansion, and industrial development. For example, the GDP Index (GDPI), value added of the transport, storage and postal sector (VATSP), and passenger turnover (TPT) all showed sustained growth over the study period, and therefore their level series failed to pass the stationarity test. Meanwhile, several industry and energy-related variables exhibited stationary characteristics in their original series. Overall, the variables exhibit different degrees of non-stationarity.

Table 5. Results of the ADF unit root tests for related variables.

Variables	ADF Statistic (Level)	p -Value	Conclusion	ADF Statistic (1st Diff.)	p -Value	Conclusion
Y (CO ₂ Emission)	2.648	0.9991	Non-stationary	−0.536	0.8868	Non-stationary
X6 (GDPI)	−2.168	0.2181	Non-stationary	−1.877	0.3429	Non-stationary
X27 (TPT)	−1.829	0.3663	Non-stationary	−0.160	0.9431	Non-stationary
X25 (CVO)	1.664	0.9980	Non-stationary	−3.079	0.0282	Stationary
X8 (VATSP)	0.166	0.9703	Non-stationary	−1.200	0.6734	Non-stationary
X12 (NEI)	7.339	1.0000	Non-stationary	6.312	1.0000	Non-stationary
X5 (STIG)	−3.054	0.0301	Stationary	−5.154	0.0000	Stationary
X21 (NMEC)	−16.386	0.0000	Stationary	−1.580	0.4938	Non-stationary
X10 (NMI)	0.284	0.9766	Non-Stationary	−1.803	0.3790	Non-stationary

The null hypothesis of the ADF test is that the series contains a unit root. A p -value below 0.05 indicates stationarity, whereas a p -value above 0.05 indicates non-stationarity.

Given the relatively small sample size ($n = 20$), some variables remained non-stationary after first-order differencing. Since the ADF test only evaluates the stationarity of individual variables and cannot identify whether stable long-term equilibrium relationships exist among them, the Engle–Granger cointegration test (table 6) was further conducted to examine the long-term equilibrium relationship between road transport carbon emissions and the key variables identified by the LASSO model. The results indicate that, under both the With Constant specification and the Constant and Trend specification, the residual ADF statistics were -7.8201 and -4.4903 , respectively, with corresponding p -values of 0.0000 and 0.0016 . Moreover, the ADF statistics under both specifications were smaller than their corresponding critical values (-4.2232 and -3.8654), further supporting the stationarity of the residual series.

Table 6. Engle–Granger Cointegration Test Results.

Specification	Residual ADF Statistic	Critical Value	p -Value	Conclusion
With Constant	-7.8201	-4.2232	0.0000	Cointegrated
Constant and Trend	-4.4903	-3.8654	0.0016	Cointegrated

Cointegration is confirmed when the residual ADF statistic is smaller than the corresponding critical value and the p -value is less than 0.05 .

The results indicate that although some variables exhibit non-stationary characteristics in their original series, road transport CO₂ emissions and the key variables selected by the LASSO model maintain a significant long-term equilibrium relationship, indicating the existence of cointegration among them. In other words, the relationships identified in this study are not simply the result of shared time trends, but indicate relatively stable long-term relationships among the variables. Therefore, the risk of spurious regression in this study is considered to be limited. Together with the results of the correlation analysis, LASSO variable selection, and multi-model robustness tests, the findings suggest that the key influencing factors identified in this study have good statistical reliability and explanatory power.

5. Discussion

On this basis, this study uses the LASSO model to identify the factors that affect transport-related carbon emissions in Qinghai Province. The results show that variables related to economic development and transport activities are still the main drivers of transport carbon emissions, while the effects of industrial structure and energy variables are more complex and show clear regional differences. This result is generally consistent with previous studies that highlight the role of economic drivers, but it also reflects the special characteristics of the mechanism in plateau regions.

5.1. Economy

The results of this study indicate that economic growth is the most important driver of road transport carbon emissions in Qinghai Province. In the correlation analysis, GDPI (Gross Domestic Product Index) showed the strongest positive correlation with road transport carbon emissions ($r = 0.97$). Consistent with the correlation analysis, GDPI obtained the highest importance score in the LASSO variable selection process, indicating a stronger contribution to road transport carbon emissions than the other variables. This indicates that economic growth is not only closely associated with changes in road transport carbon emissions, but also retains the strongest independent explanatory power after controlling for the effects of other variables. Therefore, economic growth is the

primary driving force behind the increase in road transport carbon emissions in Qinghai Province.

5.2. Transportation

In addition to economic growth, transport activities are also an important direct factor influencing road transport carbon emissions in Qinghai Province. In the LASSO variable selection results, passenger turnover (TPT), civil vehicle ownership (CVO), and the value added of the transport, storage, and postal sector (VATSP) were all retained. Among these variables, TPT and CVO exhibited importance scores second only to GDPI. This indicates that the expansion of transport activities is an important source of growth in road transport carbon emissions and also serves as a direct pathway through which economic growth influences transport carbon emissions. With economic development, stronger regional connections, and growing travel demand, road transport activities have continued to expand, leading to increased energy consumption and carbon emissions. The results suggest that this mechanism plays a prominent role in Qinghai Province. Influenced by high altitude, complex terrain, and the relatively dispersed distribution of population and economic activities, road transport has consistently played a dominant role in the regional transport system. Passenger travel, tourism activities, agricultural and livestock product distribution, as well as regional economic exchanges, all depend heavily on the road transport system. Therefore, variations in transport activity levels are more readily translated into changes in road transport energy consumption and carbon emissions.

In recent years, the implementation of the “One High and Four Bases” development strategy in Qinghai Province has promoted the development of tourism and the expansion of green organic agricultural and livestock product industries. These changes have increased both passenger and freight transport demand, resulting in sustained growth in passenger turnover and vehicle ownership and ultimately contributing to higher road transport carbon emissions. Therefore, TPT and CVO not only serve as indicators of transport activity expansion, but also reflect, to a certain extent, the indirect influence of population mobility, residents’ travel demand, and industrial development on road transport carbon emissions. The findings may offer useful implications for other high-altitude regions with similar geographical and socioeconomic conditions. In such regions, transport systems are often characterized by limited modal alternatives, dispersed settlements, and long transport distances, making road transport a key link between population centers, industrial activities, and markets.

5.3. Industry

In contrast to the consistently positive effects of economic growth and transport activity variables, both the new materials industry output (NMO) and the share of the nonferrous metal mining industry in total industrial output (NMI) showed negative associations with road transport carbon emissions. These findings suggest that industrial restructuring may contribute to alleviating the growth of road transport carbon emissions to a certain extent. Among these variables, the development of NMO may increase economic output per unit of transport activity and reduces transport demand per unit of output. Resource-based industries are characterized by relatively fixed transport routes and higher transport efficiency, thereby exerting a relatively limited effect on the expansion of road transport activities. Therefore, the transition toward higher value-added industries may reduce the reliance of economic growth on transport activity expansion and help curb the growth of road transport carbon emissions.

5.4. Energy

The relatively limited influence of energy-related variables suggests that, at the current stage, energy utilization does not directly drive road transport carbon emissions. Rather, its impact appears to operate indirectly through its interactions with industrial activities and transport demand. The LASSO results indicate that the total output value of the electric power industry (EPO) has a positive association with road transport carbon emissions. Nevertheless, its importance score is considerably lower than those of the economic development and transport activity variables. By contrast, the contribution of the nonferrous metal mining energy consumption share (NMEC) was negligible. These results indicate that energy-related factors do not play a dominant role in the formation of road transport carbon emissions in Qinghai Province. This contrasts with findings from many studies in plain regions, where energy consumption and energy structure are often identified as key determinants of carbon emissions.

5.5. Characteristics of High-Altitude Regions and Applicability of the Findings

Previous studies have shown that economic growth tends to concentrate population and economic activities, leading to increased travel demand, freight transport demand, and energy consumption, which in turn drives the growth of transport carbon emissions [24–26]. Meanwhile, energy structure optimization, improvements in energy efficiency, and the adoption of low-carbon transport technologies, such as new energy vehicles, can reduce transport carbon intensity and help mitigate the growth of transport carbon emissions [8,32]. However, the results of this study indicate that the positive drivers of road transport carbon emissions in Qinghai Province mainly stem from economic growth and the expansion of transport activities. In contrast, industrial restructuring exhibits a mitigating effect, while the independent influence of energy-related factors is relatively limited. This finding is generally consistent with the existing literature, which widely recognizes economic development as a key factor influencing transport carbon emissions [4,15]. However, compared with studies conducted in some plain regions, the influences of industrial structure and energy-related factors appear to be less pronounced. Notably, the adoption of new energy vehicles is widely recognized in the existing literature as an important strategy for reducing transport-related carbon emissions. However, unlike the findings of many previous studies, energy-related variables did not emerge as dominant explanatory factors in this study. In contrast, the new materials industry variable showed a mitigating effect on road transport carbon emissions. This finding is broadly consistent with previous studies emphasizing the importance of energy structure optimization in carbon emission reduction. However, the weaker influence of energy-related variables may reflect the fact that new energy vehicles have not yet reached a scale sufficient to substantially reshape the transport energy consumption structure in Qinghai Province.

- (1) Qinghai Province is characterized by high altitude, complex terrain, and relatively dispersed population and industrial activities. Compared with plain regions, Qinghai relies more heavily on interregional transport for resource allocation and product circulation. Similar regional development characteristics have also been reported in Yunnan, the East African Plateau, and other ecologically fragile regions [22,23]. Therefore, the mechanism linking economic growth, transport activity expansion, and transport carbon emissions may be applicable to other regions with similar geographical and development characteristics.
- (2) Road transport has long been the dominant transport mode in Qinghai Province. Passenger travel, tourism, product distribution, and resource development all depend heavily on road transport. Under conditions of limited transport alternatives and long transport distances, increases in transport demand are more likely to lead to the expansion of transport activities and, consequently, higher road transport carbon

emissions. Similar transport characteristics have also been observed in other high-altitude regions.

- (3) Qinghai Province has implemented the “One High and Four Bases” strategy. Therefore, the roles of industrial structure and energy-related factors may be region-specific and should be interpreted with caution when applied to other high-altitude regions.

5.6. Policy Implications for Low-Carbon Transport in High-Altitude Regions

The LASSO results indicate that GDPI, TPT, CVO, and VATSP are the main positive drivers of road transport carbon emissions in Qinghai Province, reflecting the important roles of economic growth, transport activity expansion, vehicle ownership growth, and transport sector development. Therefore, future transport carbon reduction policies should prioritize the effective management of transport demand arising from economic growth while continuously enhancing transport efficiency. In terms of economic development, resource-based industries should be encouraged to expand toward higher value-added processing and local utilization, thereby reducing unnecessary interregional transport demand. In terms of transport management, the continued growth of TPT and CVO highlights the need to further optimize public transport systems, tourism transport organization, and regional passenger and freight transport networks to enhance transport efficiency and reduce redundant travel demand. Meanwhile, the negative effects of NMI and NMO indicate that industrial structure optimization can contribute to mitigating the growth pressure of road transport carbon emissions. Therefore, efforts should be made to further promote the transformation and upgrading of resource-based industries while fostering high value-added industries such as the new materials industry, thereby reducing transport demand per unit of economic output. Although energy-related variables did not exhibit significant effects during the study period, Qinghai’s advantages in clean energy development provide a strong foundation for transport electrification, new energy vehicles, and related infrastructure. These measures can serve as important pathways for future low-carbon transport development and promote the coordinated advancement of economic growth, industrial upgrading, and transport emission reduction.

6. Conclusions

This study estimated road transport CO₂ emissions in Qinghai Province from 2003 to 2022 and applied LASSO regression to identify their key driving factors. The analysis was designed to test whether economic and transport-activity variables dominate over industrial and energy-related variables under plateau spatial constraints. The results show that GDPI, VATSP, CVO, and TPT have positive effects on road transport CO₂ emissions, indicating that economic expansion, transport-service growth, vehicle ownership, and passenger mobility directly increase transport-related emissions in Qinghai. Industrial and energy-related variables show more complex and indirect effects: NMI and NFMO are negatively associated with emissions, whereas NMEC has a weak positive effect. Compared with findings from many studies in plain regions, where energy structure optimization, urban expansion, and industrial agglomeration are often identified as important drivers of transport carbon emissions, road transport CO₂ emissions in Qinghai are more directly driven by economic growth and the expansion of transport activities, while the independent effects of industrial and energy-related factors appear to be relatively weaker. This difference may be related to the unique spatial development pattern of high-altitude regions. In Qinghai, population and industrial activities are relatively dispersed, and the region relies heavily on long-distance road transport. As a result, road transport CO₂ emissions are more directly driven by economic growth and the expansion of transport demand. This finding may also have implications for other high-altitude regions

characterized by ecological vulnerability and relatively limited transport options. Future low-carbon transport development in high-altitude regions should therefore combine demand management, efficient transport organization, public transport improvement, transport electrification, and coordination between spatial development and clean-energy use. Because the analysis is based on one province and annual data from 2003 to 2022, the results should be interpreted as evidence of associations and driver selection rather than universal causal effects. Future work can extend the approach to other plateau regions and finer spatial data.

7. Research Limitations and Future Research Directions

Although this study identified the key drivers of road transport carbon emissions in Qinghai Province, it still has several limitations. First, this study focuses on a single case study of Qinghai Province, and the findings require further validation before being generalized to other high-altitude regions. Second, owing to data availability limitations, the analysis is based on annual data covering the period from 2003 to 2022, which results in a relatively small sample size. Although LASSO is well suited for variable selection in small-sample settings, longer time-series data could be used to further verify the robustness of the findings. In addition, due to changes in statistical classifications and data availability, the analysis covers the period up to 2022. Future studies could use updated data to evaluate the long-term effects of key drivers and related policies.

Meanwhile, this study focuses on economic, industrial, energy, and transport activity factors, while spatial variables such as road network characteristics, land use, and regional accessibility were not incorporated into the quantitative analysis. In addition, the scale of new energy development in Qinghai Province and its impact on the transport energy consumption structure have not yet become dominant. Future research could incorporate new energy vehicle and transport electrification indicators to further assess the impacts of new energy development on road transport carbon emissions.

Future research could be extended in three directions. First, comparative studies of different high-altitude regions could be conducted to evaluate the applicability of the identified driving mechanisms. Second, spatial variables, including road network characteristics and land use patterns, could be incorporated to provide a more comprehensive understanding of regional influences on road transport carbon emissions. Third, updated data and indicators related to new energy vehicles and clean transport technologies could be used to further investigate how the drivers of road transport carbon emissions evolve during the low-carbon transition.

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Abbreviations

The following abbreviations are used in this manuscript:

GDP	Gross Domestic Product
PGDP	Per Capita Gross Domestic Product
SPIG	Share of Primary Industry in GDP
SSIG	Share of Secondary Industry in GDP
STIG	Share of Tertiary Industry in GDP
GDPI	GDP Index (Previous Year = 100)
PGDPI	Per Capita GDP Index (Previous Year = 100)
VATSP	Value Added of Transportation, Storage and Postal Services
CWI	Proportion of Coal Mining and Washing Industry
NMI	Proportion of Nonferrous Metal Mining Industry
PNG	Proportion of Petroleum and Natural Gas Extraction Industry
NEI	Total Output Value of New Energy Industry
NMO	Total Output Value of New Materials Industry
PNGO	Total Output Value of Petroleum and Natural Gas Ectraction Industry
EPO	Total Output Value of Electricity Industry
SLC	Total Output Value of Salt Lake Chemical Industry
NFMO	Total Output Value of Nonferrous Metal Industry
CWEC	Share of Energy Consumption of Coal Mining and Washing Industry
PNGEC	Share of Energy Consumption of Petroleum and Natural Gas Extraction Industry
FMEC	Share of Energy Consumption of Ferrous Metal Mining Industry
NMEC	Share of Energy Consumption of Nonferrous Metal Mining Industry
HPT	Highway Passenger Transport Volume
HFT	Highway Freight Transport Volume
THFT	Total Highway Freight Turnover
CVO	Civil Vehicle Ownership
HM	Highway Mileage
TPT	Total Passenger Turnover

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