

Advancing Emission Reduction Pathways: A Multi-Perspective Policy Analysis Based on Spatial and Social Factors

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Advancing Emission Reduction Pathways: A Multi-Perspective Policy Analysis Based on Spatial and Social Factors

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Abstract

ABSTRACT

With the rapid pace of economic development, the challenges of carbon emissions and air pollution in urban transportation, residential life, and seasonal heating have become increasingly pronounced, posing serious obstacles to sustainable urban development. While existing research has made notable progress in exploring emission reduction strategies, significant gaps remain in optimizing reduction pathways and understanding the effectiveness of policy interventions.

Air pollution in China originates from six major sectors: comprehensive, transportation, industrial, residential, agricultural, and other sectors. In recent years, the transportation and residential sectors have gained increasing policy attention, particularly during the implementation of the Three-Year Action Plan for Winning the Blue-Sky Protection Campaign and the 14th Five-Year Plan. Compared to the industrial sector—where emissions are concentrated and regulatory frameworks are well-established—emissions in the transportation and residential sectors are more decentralized, behavior-driven, and exhibit strong spatial heterogeneity. These complexities introduce substantial uncertainties in policy outcomes across different regions. Therefore, this study focuses on three key sectors: autumn and winter heating, residential sector, and transportation. It aims to analyze the emission reduction effects, synergistic interactions, and driving factors within each sector, thereby identifying sector-specific characteristics and addressing the current gaps in literature. Ultimately, the study proposes targeted optimization strategies to support cities in achieving coordinated reductions in air pollutants and carbon emissions.

In Chapter 2, this study employs a regression discontinuity design (RDD) to determine the coefficients of the effects of autumn and winter heating policies during the periods 2016-2017, 2017-2018, and 2019-2020. The findings indicate that $PM_{2.5}$ and PM_{10} are the primary

pollutants contributing to the observed reduction effect. Furthermore, a panel threshold model is utilized to estimate the critical value of the structural impact of GDP per capita on the AQI, categorizing the 28 cities as either "affluent" or "relatively less affluent." The article underscores the need for the government to enhance economic and technical support to the less affluent cities, while maintaining the current policy scope, to reduce the emission reduction disparity between regions and improve the overall effectiveness of emission reduction efforts.

Chapter 2 of this study investigates the mechanisms and applicability of cooperative emission reduction policies within the residential sector, with a particular focus on the effects of North-South disparities and socialization factors. By integrating the logarithmic mean Divisia index (LMDI), the coordinated coupling degree model (CCD), and the geographically and time-weighted regression model (GTWR), this research systematically analyzes the emission characteristics, drivers, and abatement pathways of air pollutants in the residential sector across 30 provinces in China from 2001 to 2020. The findings indicate that air pollutant emissions in southern provinces are generally higher than those in the northern regions, with this disparity widening since 2015. Within the residential sector, energy emission factors and population size exert a more significant influence on pollutant emissions than energy structure, energy intensity, synergies, or GDP per capita. The GTWR model analysis of the CCD mechanism reveals that in the Southeast, hydropower utilization and urbanization significantly enhance coordinated coupling, whereas in the West, factors such as R&D inputs, government expenditures on industrial pollution control, electricity consumption, per capita cropland area, temperature, and urbanization level are the primary contributors to enhancing the coordinated coupling degree. This study offers a valuable reference for optimizing the abatement path of the residential sector, thereby facilitating the accurate formulation of regionally differentiated abatement policies.

Chapter 3 of this study examines the transportation sector, evaluating the mechanisms and applicability of cooperative emission reduction policies, and identifying key factors contributing to regional disparities. Previous research predominantly employed scenario

analysis methods to forecast emission trends over the next 30 to 50 years, utilizing coefficients from a base year. To elucidate the status of gas emissions within the transportation sector, this paper employs panel data on 10 types of gas emissions from 2001 to 2020 to systematically analyze their emission characteristics, trends, and synergistic effects. A pollutant emission model is constructed using Kaya's constant equation and the logarithmic mean Divisia index (LMDI) method, considering synergistic effects, pollution emission intensity, energy structure, energy consumption intensity, and population size. The study's findings indicate that, except for ammonia (NH_3) and carbon dioxide (CO_2), emissions of other major pollutants in the transportation sector exhibit a declining trend. Although a synergistic relationship exists between air pollutants and CO_2 emissions, the effect of synergistic emission reduction is not significant. The transportation sector has gradually transitioned from "high emission intensity and low synergistic effect" to "low emission intensity and high synergistic effect" between 2013 and 2020. The study also reveals that in certain provinces, the transportation sector is not performing as effectively as anticipated. Furthermore, non-road mobile sources, on-road diesel vehicles, and motorcycles have emerged as primary emission sources and are focal points for policy development. Gasoline consumption is identified as the principal factor contributing to the significant increase in synergistic emission differences in transportation. These findings offer practical recommendations for policymakers to optimize emission reduction pathways in the transport sector, thereby facilitating a green transformation in the transport sector.

In summary, this study systematically examines the effects, synergies, and drivers of emission reduction policy implementation across three primary domains: urban autumn and winter heating, residential living, and transportation. It identifies the challenges and issues encountered in the emission reduction process within each domain and proposes targeted optimization strategies. The findings indicate that optimizing the energy structure, regulating population size, enhancing investment in research and development (R&D), and increasing government expenditure on pollution control are crucial measures for achieving synergistic emission reductions across multiple urban sectors. These findings serve as significant

references for urban planners and policymakers in the formulation and implementation of emission reduction policies, thereby facilitating sustainable urban development and offering valuable insights for global cities in addressing climate change and air pollution challenges.

Keywords: Autumn and winter heating policy; Residential sector; Transportation sector; Regional differences; Optimized emission reduction pathway

Chapter 1

GENERAL INTRODUCTION

Chapter 1

GENERAL INTRODUCTION

1.1 Research background

1.1.1 Air pollution on a global scale and the response

Rapid economic development and the extensive utilization of energy, while facilitating the advancement of human society, have inevitably resulted in a global escalation of air pollution. This issue is particularly evident in urban areas. As primary drivers of economic growth, cities exhibit high levels of energy consumption and a significant reliance on fossil fuels across industrial, transportation, and residential sectors. This reliance has led to a marked increase in the emission of numerous pollutants, including particulate pollutants (e.g., PM_{2.5} and PM₁₀), nitrogen-based emissions (NO_x), volatile organic substances (VOCs), and sulfur-based gases such as SO₂, which severely impact the urban environment [1]. Among other consequences, this exacerbates air pollution, with pollution-related fatalities reaching 6.7 million globally in 2019 alone [2]. Furthermore, it intensifies the adverse effects of climate change, further compromising the sustainability of urban ecosystems [3, 4].

In response, many national governments across the globe have adopted regulatory frameworks, initiatives, and strategic plans aimed at improving air quality aimed at reducing air pollution emissions and thereby enhancing human health. In 1956, the United Kingdom introduced the Clean Air Act, marking the world's earliest legislation specifically targeting atmospheric cleanliness in the world. [5]. Subsequently, Japan introduced the Air Pollution Prevention Law in 1968, targeting pollution control from industrial and transportation sources [6]. In 1970, the Clean Air Act was enacted by the United States Congress,

establishing standards for air pollutants [5]. Germany enacted the Federal Pollution Control Act in 1974 to manage and mitigate air pollution [7]. The EU's Industrial Emissions Directive came into force in 2011[8]. China introduced the Air Pollution Prevention and Control Action Plan (APPCAP) in 2013, which represented a major national-level framework comprising extensive environmental control policies as China's first nationwide framework dedicated to tackling air contamination problems [9]. Conversely, India launched its National Clean Air Program (NCAP) in 2019, aiming to reduce air pollutant concentrations in over 100 cities by 20-30% by 2024 [10]. Collectively, these measures underscore global efforts to address air pollution and establish a foundation for sustainable development worldwide.

1.1.2 Differences in policy implementation across countries

In the initial stages of air pollution regulation, the United States predominantly employed command-and-control strategies, exemplified by the Clean Air Act. However, since 1990, there has been a gradual shift towards market-based mechanisms. Significantly, the amendments made to the Clean Air Act in 1990 introduced the Acid Rain Program, which created a system for trading sulfur dioxide (SO₂) emissions. This initiative represents the world's first successful large-scale emissions trading program and has achieved substantial reductions in SO₂ emissions, serving as a model for subsequent environmental policies [11].

Europe places significant emphasis on transboundary cooperation and coordinated governance practices concerning the regulation of atmospheric pollutants. In 1979, Europe enacted the Convention on Long-Range Transboundary Air Pollution (CLRTAP), marking the world's inaugural multilateral agreement dedicated to mitigating and avoiding atmospheric contamination. This Convention has been ratified by 51 countries, including the European Union, and encompasses several protocols addressing issues such as acid rain and persistent organic pollutants. Furthermore, introduced and enforced the EU-wide carbon market mechanism known as the Emissions Trading System (ETS), recognized as the world's largest carbon market, which encompasses a diverse array of sectors, including electricity, industry, and aviation. This system facilitates cost-effective emissions reductions by

establishing a setting upper emission limit and allowing industries to exchange emission allowances under a regulated market emission allowance among themselves [12].

China, recognized as the world's largest developing nation, predominantly employs top-down administrative directives and control measures in its air pollution control strategies. Notably, the Air Pollution Prevention and Control Action Plan (APPCAP), initiated in 2013, is regarded as one of the most rigorous air pollution control policies in China's history. It establishes explicit sets explicit air quality enhancement goals and mandates strict emission reduction protocols in key regions including BTH (Beijing–Tianjin–Hebei), PRD (Pearl River Delta), and YRD (Yangtze River Delta) [13].

Nevertheless, the implementation of these policies has exposed certain challenges. Due to the uniformity in policy design and execution, regional disparities in economic development, industrial structure, and climatic conditions have frequently been neglected. This oversight has resulted in a "one-size-fits-all" governance approach that lacks the necessary specificity and flexibility [14].

In pursuit of this objective, China has been actively investigating market mechanisms to facilitate emissions reductions, supplementing traditional administrative orders and control measures. In 2021, China officially inaugurated the National Carbon Emissions Trading Market (National ETS), encompassing 2,257 key emitting units within the power sector, which collectively account for approximately 40 percent of the nation's total carbon emissions [15]. According to the "2024 National Carbon Market Progress Report," the market has successfully completed two compliance cycles, achieving a cumulative trading volume of 440 million tons and a turnover of approximately RMB 24.9 billion [16]. Furthermore, in January 2024, China re-launched its voluntary emissions trading market (CCER), thereby providing companies with enhanced options and flexibility to reduce emissions [17].

1.1.3 China Air Pollution Control Development Lineage

China's air pollution control process is characterized by typical stages and policy

orientation. Since the reform and opening of China, China's air pollution control has gone through an initial phase of end-of-pipe control (1978-1999), a transitional phase centered on total volume control and key area control (2000-2012), and a deepening phase of transition to coordinated control and high-quality development (2013-present) [18, 19].

In the initial phase, air pollution control was mainly characterized by environmental capacity control and industrial “three wastes” control, and the promulgation of the Law of China on Prevention and Control of Air Pollution for the first time in 1989 marked the entry of air pollution control into the rule of law. However, the control at this stage relied more on administrative orders and project orientation, and lacked systematic, scientific, and long-term mechanism support. At the initial stage, air pollution control was mainly characterized by environmental capacity control and industrial “three wastes” control, and the promulgation of the Law of China on the Prevention and Control of Air Pollution for the first time in 1989 marked the entry of air pollution control into the orbit of the rule of law [20]. However, the control at this stage relied more on administrative orders and project orientation, and lacked systematic, scientific, and long-term mechanism support.

After entering the 21st century, the situation of air pollution in China has become more serious with the surging energy use combined with fast-paced urban expansion, and the implementation of the “total control system” and the target management system for pollution reduction in key industries in 2005 has made the control of pollutant emissions gradually institutionalized. “Throughout the 11th Five-Year Plan period (2006-2010), SO₂ emission reduction was firstly included in the national economic development target [21]. Under the framework of the 12th Five-Year Plan, the control of pollutants such as NO_x was extended to include the reduction of SO₂. and NO_x over the course of the 12th Five-Year Plan implementation. This stage marks the gradual transition of China's air pollution management from “post-pollution management” to “source prevention and process control” [22].

The year 2013 represented a critical turning point in China's path toward modern air quality regulation [23]. The State Council promulgated the milestone document Air Pollution Prevention and Control Action Plan (APPCAP), which clearly designated BTH (Beijing–

Tianjin–Hebei), PRD (Pearl River Delta), and YRD (Yangtze River Delta) as core focus zones for integrated pollution mitigation strategies, motor vehicle regulation, and environmental information disclosure, among other multidimensional strategies. This policy, unprecedented in China, established a dual-track governance framework characterized by "hard constraints (emission reduction targets) + soft constraints (public participation)" [24]. This policy is the first of its kind in China. Subsequently, the introduction of the 2018 Three-Year Action Plan for Winning the Battle for the Blue Sky further advanced the synergistic governance model, enhancing the plan's "dual-target assessment mechanism" for the coordinated control of PM_{2.5} and ozone [25]. In summary, the evolution of China's air pollution control has progressed from isolated measures to systemic approaches, and from governance to synergy.

1.1.4 Status of air pollution in China

In recent years, the swift pace of China's economic growth has made air pollution an increasingly pressing environmental barrier to sustainable development on high-quality development. Despite the implementation of numerous national-level pollution control policies, substantial challenges persist in improving overall air quality, particularly in key regions and during periods of severe pollution, where pollution pressure remains high.

Firstly, regarding pollutant concentration, PM_{2.5} continues to be the predominant pollutant in most Chinese cities [26]. Based on the 2023 environmental bulletin released by the Ministry of Ecology and Environment, just 63.5% of China's 337 prefecture-level cities or higher achieved the required national air quality benchmarks [16]. Major hotspot regions—including the BTH area, the Fenwei Basin, and the YRD zone—continue to experience high levels of pollution.

Secondly, concerning the composition of pollution sources, China's current air pollution is characterized by a "multi-pollutant" profile [23]. The primary pollutants include fine particulate matter (PM_{2.5}, PM₁₀), volatile organic compounds (VOCs), nitrogen oxides (NO_x), and ozone (O₃). Thirdly, there is notable spatial and temporal variability in air pollution [27].

From a temporal perspective, winter is a period of heightened pollution, particularly due to coal combustion during the heating season [28], with northern cities experiencing severe pollution episodes [29]. Spatially, pollution levels decrease shifting geographically from coastal eastern zones to inland central and western parts of China [30]. However, central provinces such as Henan and Shanxi remain high-pollution areas due to their heavy industrial [31] and singular energy structures [32].

From the standpoint of urban and rural planning, the correlation between the spatial structure of cities and air pollution has become increasingly evident [33, 34]. This correlation is primarily manifested in how population density, transportation, and land use within cities influence economic growth, industrial production, fossil energy consumption, and transportation structures [35].

To sum up, the state of air pollution management in China continues to be a significant concern. Although significant improvements have been realized in some regions, there is still room for deepening structural adjustment of pollution sources, ozone management, regional joint prevention and control, and urban-rural integration. Urban and rural planning should be synergized with environmental management.

1.1.5 China's overall energy consumption and energy structure

As the largest developing nation globally, China has consistently held the position of the highest total energy consumer worldwide. The energy system not only facilitates the progression of urbanization and industrialization but is also intricately linked to air pollution and carbon emissions, making it a critical area of study for energy-related research in urban and rural planning. Regarding total energy consumption, China's energy usage has been on an upward trajectory for an extended period, although the rate of increase has decelerated in recent years (Figure 1-1, Figure 1-2). According to the China Statistical Yearbook 2021, published by the National Bureau of Statistics (NBS), the total national energy consumption in 2020 was approximately 407.295 million tons of standard coal. Coal remains the predominant source of energy in China, constituting about 67.5% of the total consumption,

while oil, natural gas, and non-fossil energy sources account for approximately 6.8%, 6%, and 19.7%, respectively (Figure 1-3). This data indicates that China continues to operate within a high-carbon energy framework predominantly reliant on coal.

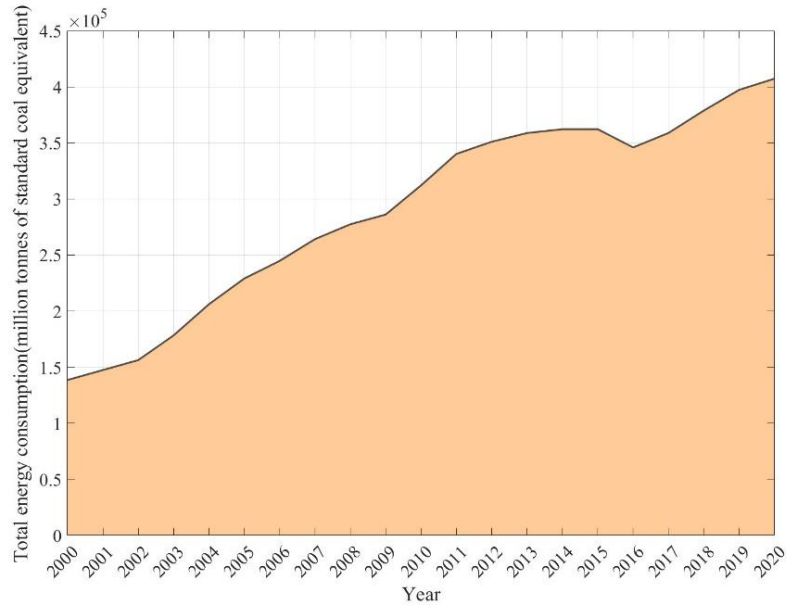


Figure 1-1 Total energy consumption in China (Data source: China Statistical Yearbook)

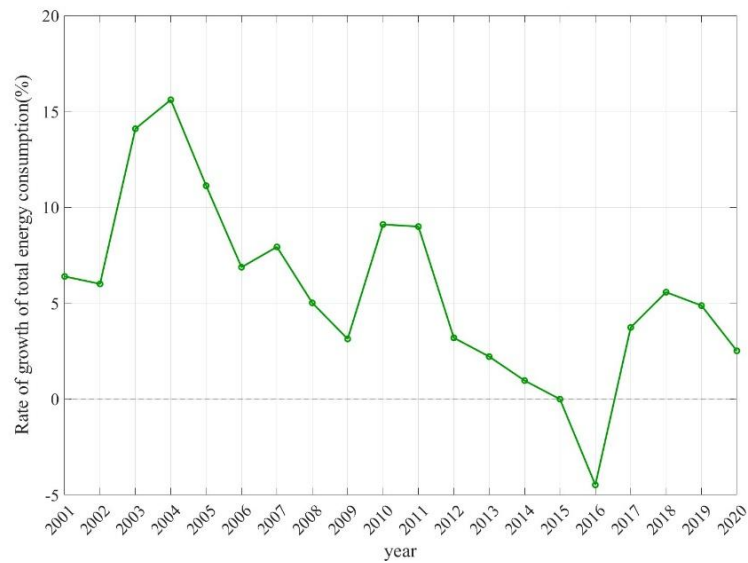


Figure 1-2 Growth rate of total energy in China (Data source: China Energy Statistical Yearbook)

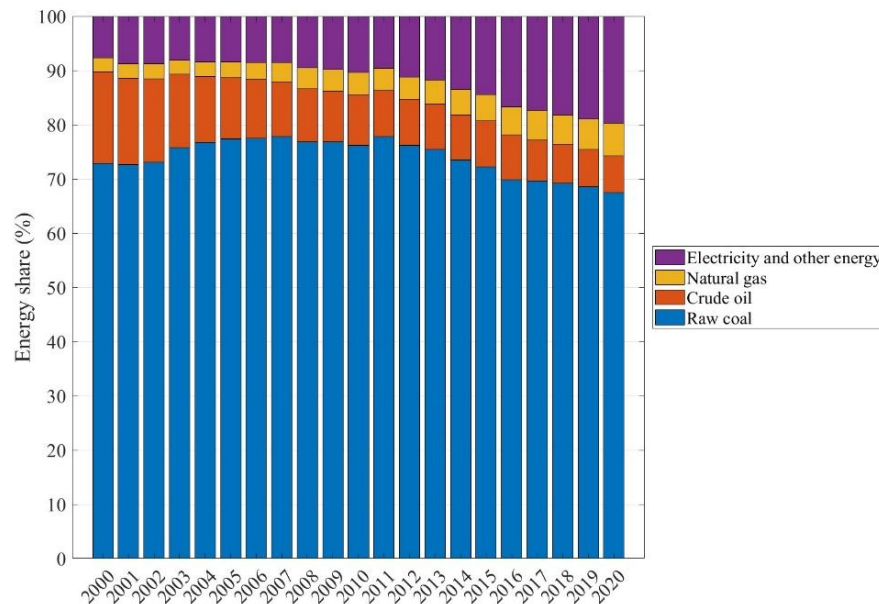


Figure 1-3 China's First Energy Composition (Data source: China Energy Statistical Yearbook)

Nevertheless, the transformation of the energy structure continues to encounter several challenges. Firstly, the absolute consumption of coal remains elevated, particularly in the western regions and cities characterized by heavy industry, where coal's fundamental role in energy supply is challenging to fully replace in the short term [36]. Secondly, although natural gas is considered a transitional energy source, its penetration remains insufficient in the central and western regions and rural areas due to infrastructure layout and import dependency, complicating its ability to fully replace bulk coal usage, especially during the winter heating season [37].

From an urban-rural perspective, energy consumption exhibits a dichotomous pattern of "urban clean, rural high-carbon." In urban areas, enhanced infrastructure and policy constraints have led to higher utilization of clean energy sources such as electricity and

natural gas. In contrast, rural areas continue to rely on inefficient and highly polluting energy sources, including biomass and loose coal [38].

In conclusion, China's overall energy consumption is still predominantly coal-based, and although the energy structure is improving, its high-carbon characteristics have not fundamentally changed. To achieve decarbonization of the energy structure, it is imperative to strengthen clean energy substitution, enhance terminal energy efficiency, and promote regional energy synergy alongside urban-rural integration and transformation.

1.2 Previous Studies

1.2.1 Progress in overall research

During the 1950s, the national government introduced a policy for winter heating that provided the public with free coal. However, due to financial limitations, this policy was exclusively applied in northern China, leading to a prolonged dependence on coal for winter heating in that region [39-40]. Since 2013, the government has introduced several air pollution control policies, including a prohibition on new thermal power plants in the Beijing-Tianjin-Hebei region, restrictions on motor vehicle usage, and a reduction in iron and steel production capacity, among other strategies to decrease pollutant emissions [41]. Subsequently, scholars have conducted empirical assessments of the emission reduction effects of each individual policy measure [13].

In 2016, the government prioritized the implementation of the policy within the "2+4" city cluster, which served as the focal area, resulting in a marked improvement in air quality in the Beijing-Tianjin-Hebei region and extending the treatment scope to 20 cities. The 2017-2018 Comprehensive Control of Air Pollution in Autumn and Winter Campaign further broadened the regional joint prevention and control efforts to encompass 28 cities. Relevant studies have demonstrated that air pollution exhibits significant spatial spillover effects [42-44] and have recommended expanding the policy's application scope to enhance treatment efficacy [45]. However, some studies caution that indiscriminate expansion may diminish the

policy's marginal benefits [46]. In this context, research has shifted focus from "whether policies are effective" to "under what conditions are policies more effective." Scholars have increasingly recognized that the effectiveness of regional joint prevention and control policies is contingent not only on technological pathways and emission reduction intensity but also on the comprehensive influence of inter-regional industrial structure, energy structure, governance capacity, and financial resource allocation, among other factors. Additionally, the spatial expansion of regional policies encounters a significant challenge, namely, how to reconcile the interests of central cities and neighboring regions concerning emission reduction responsibilities, industrial transfer, and resource allocation.

The sources of air pollution are varied and can generally be categorized into six primary sectors: the integrated sector, the transportation sector, the agricultural sector, the residential sector, the industrial sector, and other sectors. From a policy intervention perspective [47], the government has implemented a total of 688 policies aimed at pollution prevention and control. The integrated sector is the most targeted, accounting for 36.19% (249 policies) of these interventions, followed by the transportation sector (151 policies, 21.95%), the industrial sector (96 policies, 13.95%), and the residential sector (89 policies, 12.94%). Within the industrial sector, the primary sources of pollution are concentrated in centralized high-emission units such as coal-fired power plants. For these units, there exist well-established policy tools and assessment systems for emission control, resulting in a substantial body of relevant studies. Conversely, the transportation and residential sectors have increasingly become focal points for control efforts in recent years, particularly during the Three-Year Action Plan for Winning the Blue-Sky Protection and the 14th Five-Year Plan period, during which the frequency of policy implementation has risen significantly.

The transportation sector's emission sources are characterized by considerable regional mobility and structural complexity, encompassing multiple variables such as vehicle type, usage intensity, and fuel composition. In contrast, the residential sector is heavily influenced by individual behavior, exhibiting significant regional heterogeneity, with pronounced issues related to decentralized heating and the use of biomass fuels. These characteristics result in

substantial uncertainties and spatial variations in the governance effects of the transportation and residential sectors within the current policy framework. Consequently, this paper selects the transportation and residential sectors as the focus of research, aiming to address the gap in the study of synergistic emission reduction mechanisms in these sectors and to propose more targeted regional governance strategies.

1.2.2 Rationalization of the scope of implementation of the Autumn/winter policy

Since November, centralized heating has been implemented in northern regions, prompting government control measures to focus on the autumn and winter seasons to mitigate the issue of high pollutant accumulation during this period. Li [48] highlights that while regional joint prevention and control can reduce pollution, the high proportion of secondary industries, dense population, and frequent production activities remain the primary reasons for the persistence of haze. The effectiveness of related policies in combating haze varies across cities. Liu [49] finds that although air pollution more significantly affects rural areas, the transition from coal to natural gas offers substantial health benefits that far outweigh its costs. The synergistic effects of carbon emissions and air pollution also differ significantly between economically developed and less developed regions [50]. This indicates that optimizing air pollution control policies for future autumn and winter seasons should emphasize "differentiated control" and "site-specific" implementation strategies. The implementation strategy should focus on "differentiated control" and "localized" approaches, considering factors such as industrial structure type, energy structure dependence, residential heating mode, and historical pollution load. For instance, in the Beijing-Tianjin-Hebei region and its neighboring areas, it is recommended that while maintaining the emission reduction intensity of core cities, more flexible emission reduction targets should be established for peripheral cities on the pollution transmission belt to avoid the negative externalities of a "one-size-fits-all" policy. Therefore, the primary focus of this study is the rationality of the scope of the autumn/winter heating policy and the boundaries of its implementation.

1.2.3 Synergized emission reductions in the residential sector

The Three-Year Action Plan for Winning the Battle for the Blue Sky (2018-2020) further advocated for the reform of rural heating methods and the promotion of the construction of "coal-to-electricity" supporting power grids and infrastructure [51]. The 14th Five-Year Plan, introduced in 2021, set forth specific goals to be achieved by 2025, including a target of over 86% for the comprehensive utilization of rural straw, 50% photovoltaic coverage in urban public institutions and new factories, and an increase in the renewable energy substitution rate in urban buildings to 8%. [52]. In 2023, the Chinese government introduced a pilot program for rural energy reform, aiming to achieve a renewable energy share of more than 30% in 15 pilot counties by 2025 [53]. These policies not only reflect the government's strategic transition in addressing structural pollution issues but also signify a shift from single-pollution control to multi-objective synergistic management. Notably, the continued promotion of the "coal-to-electricity" policy has significantly contributed to transforming the energy structure of residents' living conditions in the northern region into a cleaner one. However, these policies have encountered several challenges, such as insufficient natural gas supply capacity and limited affordability for rural residents, which have led to "backing out" in some areas, thereby affecting the long-term effectiveness and sustainability of the policies.

Meanwhile, the China Center for Environmental Politics and Economic Policy Research (CCEEPR) has proposed a definition of dual co-benefits arising from simultaneous efforts in curbing air pollutants and cutting carbon emissions [54]. Firstly, in the process of controlling greenhouse gas (GHG) emissions, the discharge of additional regional atmospheric contaminants (e.g., SO₂, NO_x, CO, VOC, and PM) can be simultaneously reduced. Secondly, the process of managing local pollutant emissions and engaging in ecological construction can also lead to the reduction or absorption of CO₂ and other pollutants. Consequently, the feasibility of achieving CO₂ emission reduction and promoting sustainable development while mitigating air pollution, as well as the existence of synergistic emission reduction implementation outcomes, driving forces behind these outcomes, and optimization approaches for improving policy effectiveness, have garnered significant attention within the

academic community. Based on the aspects, this study focuses on the second issue, namely, the mechanism and applicability of the integrated emission mitigation strategy targeting residential energy and fuel consumption behaviors.

1.2.4 Synergized emission reductions in the transportation sector

The transportation sector is intrinsically linked to the daily lives of residents. Alimujiang highlighted the benefits of electrically powered private cars, commercial taxi fleets, and public transit buses in mitigating CO₂ and ambient pollutant discharge levels within the Shanghai metropolitan area [10]. However, the research lacked a thorough economic evaluation of the fiscal impacts of the extensive adoption of electric vehicles, particularly those concerning the development and upkeep of infrastructure. Jiao quantified co-mitigative outcomes related to simultaneous CO₂ abatement and air quality improvements in urban transport systems in Guangzhou, assessing emissions across different urban transportation subsectors [55]. Nonetheless, the research did not sufficiently consider the differences in transportation infrastructure, energy usage, and pollution management strategies across regions. Duan assessed traditional governance strategies for the road transportation sector in Chongqing, finding that modal shifts effectively reduced air pollutants and carbon dioxide emissions in the short term, while underscoring the importance of cleaner electricity production for the medium- and long-term development of electric vehicles [56]. Guo investigated energy consumption and emissions in the Beijing-Tianjin-Hebei region, concluding that optimizing the energy structure is the most effective strategy for reducing emissions from the road transport and aviation sectors [57]. Dong examined the impact of CO₂ emission reduction on air pollution in the road transport sector in Zhengzhou using the LEAP framework and scenario simulation methodology [50]. Fu's study developed a framework for scenario analysis, demonstrating that promoting new energy vehicles, energy decarbonization, and compact city development can achieve synergistic reductions in air pollution and greenhouse gases by 2050 [58]. These studies mainly depend on scenario analysis driven by models, which assist policymakers by offering possible results for different policy choices, thus enabling more informed decision-making. While this strategy

is largely reliant on model predictions and policy assumptions, it may fail to account for discrepancies with actual policy changes, which could influence the validity of the results analyzed. Consequently, we contend that it is imperative to examine the mechanism of action and applicability of collaborative emission reduction policies in the transportation sector based on historical data.

1.3 Research Objectives

As discussed in Section 1.2.1 Progress in Overall Research, air pollution in China originates from six major sectors: the comprehensive, transportation, industrial, residential, agricultural, and other sectors. In recent years, the transportation and residential sectors have received increasing policy attention, particularly during the implementation of the Three-Year Action Plan for Winning the Blue-Sky Protection Campaign and the 14th Five-Year Plan. Compared to the industrial sector—where emissions are largely concentrated in coal-fired power plants and supported by well-established regulatory frameworks, emissions from the transportation and residential sectors are more decentralized, behavior-driven, and exhibit significant spatial heterogeneity. These characteristics contribute to considerable uncertainties and regional disparities in policy effectiveness. Therefore, this study quantitatively evaluated policy effectiveness of three key areas—heating policy, the residential sector, and the transport sector to determine the priority order of implementation across different regions with the aim of formulating region-specific strategies for the coordinated reduction of air pollutants and carbon emissions.

This study investigates the optimization of emission abatement pathways across three dimensions:

1. **Centralized Heating Policy Evaluation:** Analyze the emission reduction effects of government-led centralized heating systems in northern Chinese cities. The study identifies inter-city disparities and assesses whether current governance boundaries require adjustment to improve policy equity and effectiveness.

2. **Residential sector:** Explore diverse residential heating behaviors beyond centralized systems. The research examines the influence of socio-economic factors on household-level emission behaviors, aiming to inform tailored mitigation strategies.
3. **Transport Sector:** Investigate regionally coordinated emission control strategies within the urban transportation sector. The focus is on identifying key drivers of spatial disparities in transport emissions and developing region-specific planning measures for integrated air quality and carbon governance.

1.4 Research structure

Chapter 1 introduces the foundational aspects of China's air pollution policy, including the historical development of air pollution measures tackling, the present conditions of air quality management, and the overall energy use and structural trends. Additionally, it elucidates fundamental concepts such as policy synergy. Based on a comprehensive literature review, the chapter delineates the specific objectives of this study and outlines a preliminary research program.

In Chapter 2, the article applies the regression discontinuity approach (RDD) to estimate the effectiveness of policies across segmented timeframes: 2016–2017, 2017–2018, and 2019–2020. The results reveal that fine particulate matters —specifically $PM_{2.5}$ and PM_{10} — serve as the dominant pollutants driving the observed mitigation trends. Furthermore, a panel threshold modeling technique is applied to identify the GDP per capita tipping point at which structural effects on AQI become significant.

In Chapter 3, this study analyzes the emissions of 10 gases in the transportation sector utilizing panel data spanning 2001 to 2020 and integrating the Kaya identity along with the logarithmic mean Divisia index (LMDI) technique, and explores in depth the characteristics of the emissions, the trend of change and the synergistic effect. On this basis, a pollutant emission model covering including emissions intensity, energy portfolio structure, per capita energy usage, and population size was constructed, which takes synergistic effects into full

consideration. It was found that, except for NH_3 and CO_2 , the emissions of other pollutants in the transportation sector showed exhibited a consistent downward trajectory. Although there is some synergistic effect between air pollutants and CO_2 emissions, this synergistic reduction is not obvious. From 2013 to 2020, the emission status of the transportation sector underwent substantial transformation, shifting from a pattern of high pollutant output with minimal coordination to one marked by low emissions and strong synergistic performance.

Chapter 4 of the study examines the pollution features, influencing drivers, and corresponding control policies of air pollution within the residential sector across 30 provincial-level administrative units in China over the 2001–2020 period. This analysis adopts a combination of LMDI decomposition, CCD framework, and GTWR spatial-temporal modeling for comprehensive analysis. The GTWR model specifically evaluates the influence of factors such as hydropower development, urbanization level, research and development financial input—including public funding for industrial emission abatement—electricity usage, cultivated land availability per person, and ambient temperature, and urbanization level on the CCD.

Chapter 5 presents a comprehensive summary of the study's principal findings, focusing on the evaluation of the implementation scope and governance boundaries of the autumn and winter heating policy. It also examines the synergistic emission reduction pathways within the transportation sector, as well as those spanning both the transportation and residential sectors. Furthermore, the chapter discusses academic contributions, innovations, and potential future research directions stemming from the study.

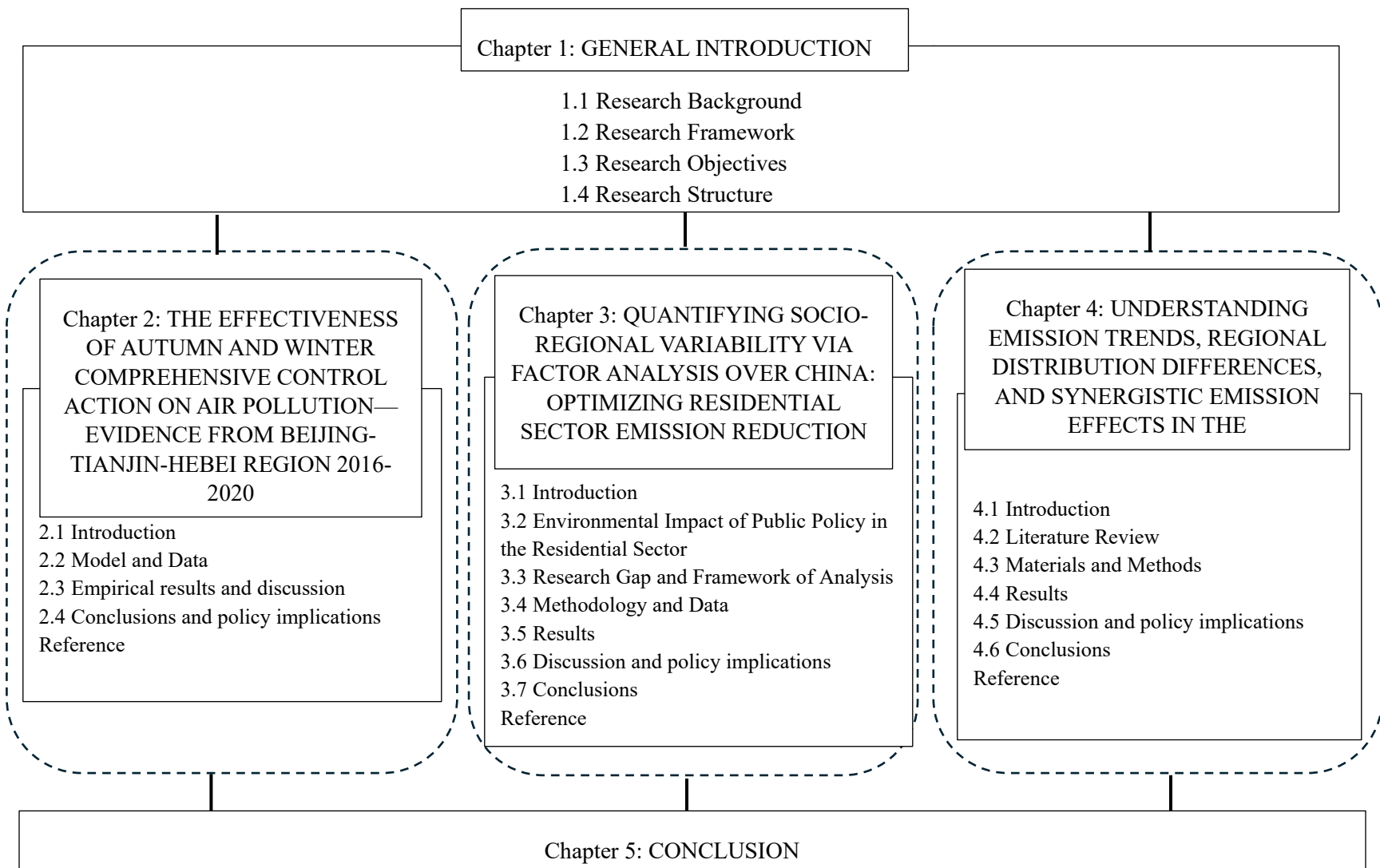


Figure 1-4 The main flow chart of this study

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Chapter 2

THE EFFECTIVENESS OF AUTUMN AND WINTER COMPREHENSIVE CONTROL ACTION ON AIR POLLUTION—EVIDENCE FROM BEIJING-TIANJIN- HEBEI REGION 2016-2020

Chapter 2

THE EFFECTIVENESS OF AUTUMN AND WINTER COMPREHENSIVE CONTROL ACTION ON AIR POLLUTION—EVIDENCE FROM BEIJING-TIANJIN-HEBEI REGION 2016-2020

2.1 Introduction

The economy developed rapidly with China's reform and opening up in 1978. Total primary energy consumption rose from 620.46 million tons of standard coal to 3644.19 million tons of standard coal. This rise has been particularly pronounced since 2000, resulting in China's per capita energy consumption quadrupling by 2020 compared to the levels observed in 1980 [1]. And for the past 40 years, coal has always maintained a 70% share.

According to the results of the seventh census to be implemented in 2020 [2], the population growth rate in the Beijing-Tianjin-Hebei region was higher than the national average in the past 30 years. The Beijing-Tianjin-Hebei region, situated in northern China between latitudes 36°03'N to 42°40'N and longitudes 113°27' to 119°50'E, experiences cold and dry winters. In the 1950s, the central government implemented a winter heating policy by providing free coal to the public. However, due to financial constraints, this policy was limited to northern China [3,4]. As a result, the regions of the north began relying on coal for heating in winter. Notably, coal consumption in the vicinity of Beijing, Tianjin, and Hebei has surged to 1.5 billion tons, accounting for 43% of the national total [5]. This situation addresses the challenge of enhancing air pollution and safeguarding the well-being of residents, which has emerged as a significant area of focus among researchers.

The earliest policy on air quality improvement began with the 2008 Beijing Olympics [6]. Many studies started in 2012, characterized by the initial recognition of the pressing nature of the issue and appeals for governmental intervention [7-9]. A proposed approach [10] involves establishing unified regulatory standards and implementing a technical monitoring

system within the joint prevention and control area framework. They insist that participating regions can adhere to a set of guidelines, ensuring consistency and coherence in pollution prevention and control efforts. Also, some other articles endeavor to put forth resolutions to tackle the problem effectively [11-14].

Since 2013, the government began a plan to reduce emissions by banning the establishment of new thermal power plants in the Beijing-Tianjin-Hebei region, reducing motor vehicle pollution through vehicle restrictions, and compressing steel production [15]. After this, a considerable body of research has emerged, explicitly examining policy evaluations of various individual action programs [16].

In 2016, the government alleviated air pollution in the Beijing-Tianjin-Hebei region, with “2+4” cities as the focus of observation, while expanding the scope of policy implementation to 20 cities. In the 2017-2018 Autumn and Winter Comprehensive Control Action on Air Pollution (hereafter referred to as the 2017-2018 action plan), the government expanded the regional joint prevention system to 28 cities. With this, many studies have considered the spatial spillover of air pollution [17-19] and recommended expanding the scope of policy implementation to enhance its effectiveness, leading to improved environmental outcomes [20]. However, prior studies suggest blind expansion can easily lead to a decline in policy effects [21]. Therefore, it is worth studying whether improving air quality in the Beijing-Tianjin-Hebei region works.

Meanwhile, the policy approach of focusing on controlling air pollution during the autumn and winter seasons in northern China, mainly due to the initiation of heating in November, is aimed at alleviating the severe air pollution during this period. According to Li, regional joint prevention can reduce air pollution. Still, the industrial structure with a considerable proportion of secondary industries, the concentration of population, and the production activities will aggravate haze pollution in China [22].

The impact of policy implementation exhibits variation across different cities within the region. For example, air pollution significantly impacts rural areas, but the long-term health benefits outweigh the cost of transitioning from coal to natural gas [23]. Different co-reduction effects of air pollutants and CO₂ reduction exist in economically developed and

less developed regions [11]. However, studies need to show how economic development level can affect the effectiveness of policies.

2.2 Objective of this study

The first main objective of this article is to examine whether the autumn and winter special plan implementation is still adequate to date. Many prior studies have focused on the period of 2013-2017. Since 28 cities became the joint prevention and control area in 2017, there needed to be more ongoing concern or discussion about the scope of policy implementation. Therefore, this study evaluated the policy effectiveness among 28 cities for 2017-2018 and 2019-2020 to examine the ongoing effectiveness changes.

Secondly, prior research has explained many social factors influencing environmental quality. For instance, financial expenditures for environmental protection [24], the proportion of secondary industry [25], conventional energy generation [26], and economic development [27]. Have these societal factors affected the implementation of the air pollution policy? Therefore, the study's second objective is to identify the social factors that influence the effects of the action plan and make recommendations for the continued implementation of the policy in the future.

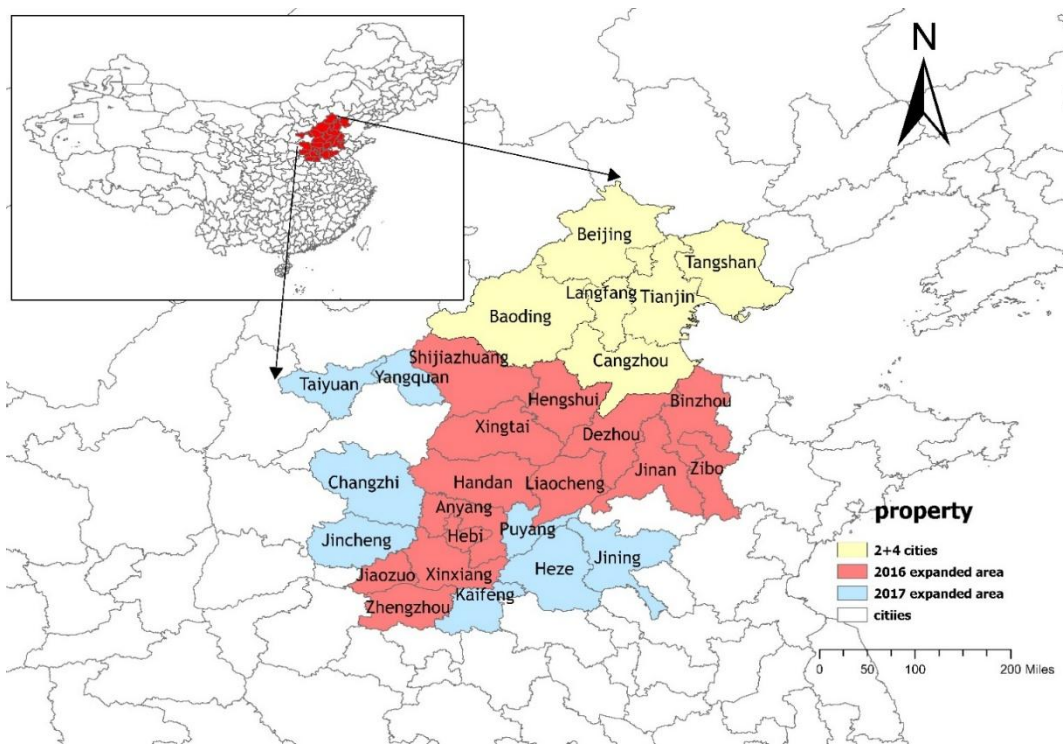
2.3 Model and Data

2.3.1 Study region and timeline

Before 2016, “2 + 4” cities were the air pollution policy implementation area, which was expanded to 20 cities in 2016 and 28 cities in 2017 (Table 2-1). They were implementing the scope of “2 + 4” cities, namely Baoding, Beijing, Cangzhou, Langfang, Tangshan, and Tianjin. In 2016, the implementation scope expanded to 20 in newly added Shijiazhuang, Handan, Xingtai, and Hengshui in Hebei province, Jinan, Zibo, Dezhou, Binzhou, Liaocheng in Shandong province, Zhengzhou, Anyang, Hebi, Xinxiang, Jiaozuo in Henan province. In 2017, the scope was further expanded and included the following eight cities: Taiyuan, Yangquan, Changzhi, and Jincheng in Shanxi province; Jining, Heze in Shandong province; Kaifeng and Puyang in Henan province (Figure 2-1).

Table 2- 1. Policy Timeline

Policy period	Start time	Scope
2016.10-2017.10	2016.11.01	20 cities
2017.10-2018.03	2017.10.01	28 cities
2019.10-2020.03	2019.10.01	28 cities

**Figure 2-1. Policy Implementation Scope**

2.3.2 Data source

The pollutant-related data used in the study was obtained from the China Air Quality Online Monitoring and Analysis Platform (<http://www.aqistudy.cn/historydata/>). This platform provides access to daily average value of various pollutants, including fine particulate matter (PM_{2.5}), inhalable particulate matter (PM₁₀), sulfur dioxide (SO₂), carbon monoxide (CO), ozone (O₃) and nitrogen dioxide (NO₂). Specifically, the dataset includes Air Quality Index (AQI)

records for 28 cities across three key periods: September 1, 2016 to April 30, 2017; September 1, 2017 to April 30, 2018; and September 1, 2019 to April 30, 2020. These measurements serve as indicators of air quality and are crucial for assessing the impact of air pollution. Meteorology-related data, including daily average wind speed, average temperature, and average rainfall, were sourced from the National Environmental Protection Administration of China. These meteorological factors play a significant role in understanding atmospheric conditions and their influence on pollution levels. GDP per capita data for each city is obtained from various official sources such as the China City Statistical Yearbook, Municipal National Economic and Social Development Statistical Bulletin, and Provincial and Municipal Regional Statistical Yearbooks.

2.3.3 Model setting

2.3.3.1 RDD model

This study applies the Regression Discontinuity Design (RDD) model to analyze policy effects. The RDD model was proposed by Thistlethwaite and Campbell in 1960. It has been widely used in research related to socioeconomic factors and air pollution [28-34].

In this study, the policy implementation is treated as a quasi-natural experiment, where policy implementation leads to changes in AQI. The official implementation date of the policy was first determined, using this date as a cutoff. Completing the Autumn and Winter action plan is considered an external intervention. To examine whether there were discontinuous changes in air quality. The air quality before the action plan is regarded as the control group, while the air quality after the action plan is regarded as the treatment group. The model is constructed as follows:

$$Y_{it} = \alpha + \delta Treatment_{it} + \sum_{j=1}^4 \beta_j (t - c)^j + Treatment_{it} \sum_{j=1}^4 \gamma_j (t - c)^j + \mu X_{it} + \varepsilon_{it} \quad (2-1)$$

2.3.3.2 Threshold model

This study used Threshold Regression (TR) to analyze differences in the policy implementation effect in different cities. This model was proposed by Hansen [35]. The basic idea of the model is to estimate the possible values of the inflection points, and then test them to find the corresponding confidence intervals. The article tests the effect of changes in per capita GDP on AQI. By estimating these parameters, the article aims to explain the impact of changes in per capita GDP on AQI levels at different income levels.

The model is constructed as follows:

$$V_{it} = \alpha\mu_{it} + \beta_1'F_{it}I(q_{it} \leq c) + \beta_2'F_{it}I(q_{it} > c) + e_{it} \quad (2-2)$$

where V_{it} denotes the outcome variable, which is annual AQI. q_{it} represents a variable for city i at time t . μ_{it} denotes the control variable that has a significant control variable effect on the explanatory variable, F_{it} is also a threshold variable that varies with the explanatory variable. c is the specific threshold value e_{it} means the error. $I(\cdot)$ is an indicative equation, which takes 1 on a set and 0 elsewhere. The article sets the outcome variable as the yearly AQI for each city. Set the time as the threshold variable, when $q_{it} \leq c$ the equation becomes:

$$V_{it} = \alpha\mu_{it} + \beta_1'F_{it} + e_{it} \quad (2-2.1)$$

when $q_{it} > c$ the equation changes into

$$V_{it} = \alpha\mu_{it} + \beta_2'F_{it} + e_{it} \quad (2-2.2)$$

2.4 Empirical results and discussion

2.4.1 RDD

The article describes air quality by AQI and regresses rain, temperature, and wind as covariates. There is a large gap between the maximum and minimum values of PM_{2.5} and other pollutants, indicating significant differences in air quality between cities.

2.4.1.1 Results

2.4.1.2 RDD results

When regressing with RDD, the article added wind speed, rainautumn, and average temperature as covariates, and the regression results are as follows (Table 2-3). The data show that the effect of the policy was more significant in 2016-2017 than in 2017-2018. The policy factor increased in the following autumn and winter action plan of 2019-2020 compared to 2017-2018. The 2017-2018 implementation was expanded to 28 cities from 20 in 2016-2017, but such an expansion did not increase the emission reduction factor. In the 2019-2020 action plan, although the number of cities implemented is the same as in 2017-2018, the role of emission reduction has risen significantly. Therefore, does the implementation of this policy need to be further expanded? If the scope remains unchanged at 28 cities, from which city will the increase in implementation effect come?

2.4.1.3 Heterogeneity analysis

Data analysis shows that the emission reduction contribution is mainly from particulate matter ($PM_{2.5}$, PM_{10}) reduction, where SO_2 , NO_2 , and O_3 reduction are unstable (Table 2-4). This also confirms that the goal of the autumn and winter action plan is to reduce $PM_{2.5}$.

2.4.1.4 Robustness test

2.4.1.4.1 Covariant test

Because atmospheric pollution is influenced by meteorological factors [21,36,37], the article tests whether there is a jump in wind speed, rainautumn, and average temperature around the cutoff (Table 2-5). If there is a jump, it will be excluded from the RDD regression results.

2.4.1.4.2 Bandwidth test

The Bandwidth determines the number of samples entering the regression, affecting the RDD results. Therefore, we performed a sensitivity test for window width and found that

neither the 20-day bandwidth nor 30, 40, 50, or 70 affected the significance of the RDD results.

2.4.1.4.3 Placebo test

For the placebo test, the article shifted the same sample forward by 60 days and backward by 60 days. As shown in Table 6, no matter how the cutoff is moved, there is no significant reduction. This way, we can determine whether the RDD regression results have a considerable reduction effect.

2.4.2 Threshold model

The article also collects GDP per capita, second industry contribution to GDP, percentage of secondary industry, electricity consumption, innovation input, and city green area as threshold regression variables for the threshold value test to further analyze the heterogeneity of policy effects. And the annual average AQI and PM_{2.5} from 2016-2020 as outcome and covariate variables, respectively.

2.4.2.1 Model test

Through the calculation, the article found that except for the per capita GDP (Table 2-7), the total output value of the secondary industry, the proportion of the secondary industry, electricity consumption, and the green area did not show the threshold value. The per capita GDP threshold is 65512 and passed the likelihood ratio test, indicating a significant shift in AQI levels when the average annual income reaches 65512 RMB.

2.4.2.2 Threshold model results

The regression results show that the slope of air quality is 0.889 when GDP per capita is less than or equal to 65,512 RMB, and the change in pitch of air quality is 0.971 when GDP per capita is more significant than 65,512 RMB (Table 2-8).

2.4.2.3 Heterogeneity analysis

Table 2-2 Descriptive statistics of variables

Variable	Unit	Obs	Mean	Std. dev.	Min	Max
AQI	index	3,416	94	37.9375	0	271
PM _{2.5}	µg/m ³	3,416	55	30.16138	0	224
PM ₁₀	µg/m ³	3,416	138	93.15412	1	256
SO ₂	µg/m ³	3,416	27	23.0779	1	94
CO	mg/m ³	3,416	12	9.175611	1	79
NO ₂	µg/m ³	3,416	45	17.5338	0.7	104
O ₃	µg/m ³	3,416	138	81.6191	1	252
Rain	mm	3,416	2	5.340172	0	78.63311
Temp	°C	3,416	17	8.257185	-4.942079	31.53667
Wind	km/h	3,416	2	0.6673304	0.5708576	5.28238

Note: The Air Quality Index (AQI) is a composite indicator used to evaluate and communicate air quality levels to the public. In China, AQI is calculated based on six major air pollutants: PM_{2.5}, PM₁₀, SO₂, NO₂, CO, and O₃. The calculation method follows the official technical regulation HJ 633–2012 issued by the Ministry of Environmental Protection. Detailed calculations are presented in the supplementary information.

Table 2-3. The effect of Autumn and Winter action on AQI

Polynomial order	First	Second	Third	Forth
2016-2017 coefficient	-31.59***	-3.296	-8.28	-41.68***
(20cities)	-4.55	-4.572	-5.777	-7.706
Observations	2,440	2,440	2,440	2,440
2017-2018 coefficient	-14.48***	-13.77**	-25.72***	-52.67***
(28cities)	-4.497	-5.538	-7.255	-10.53
Observations	3,388	3,388	3,388	3,388
2019-2020 coefficient	-33.01***	-47.61***	-21.51	18.04
(28cities)	-7.506	-10.58	-16.34	-23.59
Observations	3,388	3,388	3,388	3,388
Bandwidth	60 days	60 days	60 days	60 days
Weather control	Y	Y	Y	Y

Note: ***, **, * represent $p < 0.01$, $p < 0.05$, $p < 0.1$, respective

Table 2-4. Robustness test of different pollutants

	PM _{2.5}	PM ₁₀	SO ₂	CO	NO ₂	O ₃
2016-2017	-31.79*** (5.033)	-56.76*** (8)	-0.15 (2.248)	-0.579 (1.415)	-0.389 (2.314)	-12.93*** (3.848)
Observations	2,440	2,440	2,440	2,440	2,440	2,440
2017-2018	-10.75*** (3.934)	32.28** (14.79)	4.403 (3.356)	0.979 (0.84)	-8.063*** (2.453)	23.03* (12.67)
Observations	3,388	3,388	3,388	3,388	3,388	3,388
2019-2020	-9.003 (6.255)	-32.76*** (10.43)	2.605* (1.334)	0.29 (0.384)	1.402 (3.13)	-11.04 (7.564)
Observations	3,388	3,388	3,388	3,388	3,388	3,388
Weather control	Y	Y	Y	Y	Y	Y

Table 2-5. The discontinuity of covariant

	2016-2017	2017-2018	2019-2020
Wind	-0.0421 (0.121)	-0.0581 (0.0875)	-0.918*** (0.447)
Rain	0.826*** (0.129)	2.026** (0.955)	0.294*** (0.0455)
Temp	-4.800*** (0.619)	-0.331 (0.461)	1.826*** (0.447)
Observations	730	3,354	3,377

Note: ***, **, * represent $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively.

Table 2-6. Robustness test of different cutoffs

	2016-2017		2017-2018		2019-2020	
	-60 days	+60 days	-60 days	+60 days	-60 days	+60 days
Coefficient	12.90*** (4.528)	115.2*** (13.96)	-4.52 (5.440)	53.56*** (6.235)	24.03*** (7.420)	18.43*** (5.054)
Weather control	Y	Y	Y	Y	Y	Y
Observations	2,420	2,420	3,267	3,388	3,267	3,388

Table2-7. Threshold effect (bootstrap = 400)

Threshold	RSS	MSE	F	P	1%	5%	10%
Single	995.7700	9.2201	15.72	0.0825	14.4641	19.5436	25.6357

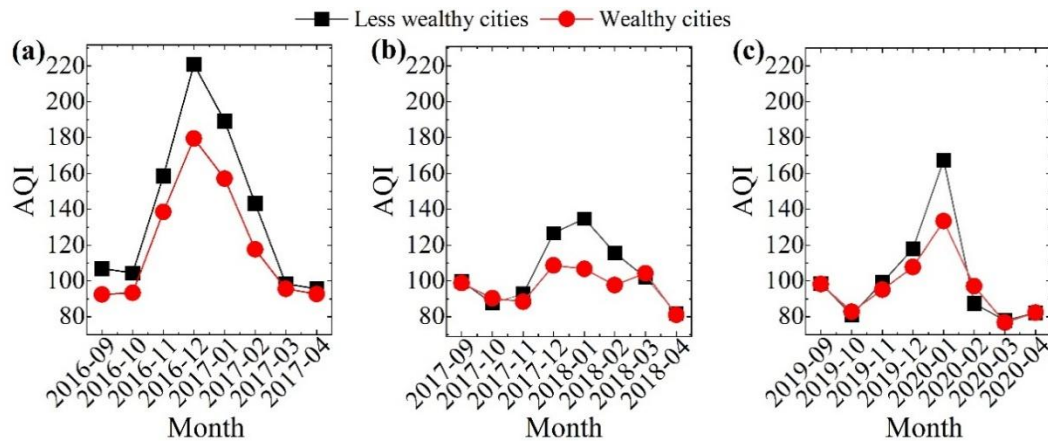
Table 2-8. Fixed effects (within) regression

VARIABLES	AQI
Rain	924 (2,131)
Temp	13.75*** (2.919)
Wind	-3.823 (3.847)
Pgdp $\leq$ 65512	0.889*** (0.0423)
Pgdp $>$ 65512	0.971*** (0.0434)
Constant	-124.5** (53.76)
Observations	112
R-squared	0.878

Note: ***, **, * represent $p < 0.01$, $p < 0.05$, $p < 0.1$, respectively

Table 2-9. Comparison of policy coefficients for Wealthy and Less wealthy cities

	2016- 2017 Wealthy	2016- 2017 Less	2017- 2018 Wealthy	2017- 2018 Less	2019- 2020 Wealthy	2019- 2020 Less
Coefficient	- 17.42*** (5.95)	- 16.56** (6.723)	- 38.07*** (8.747)	- 12.84** (6.191)	- 19.75*** (6.69)	- 24.60** (9.94)
Observations	1,098	2,178	1,210	2,178	1,210	2,178
Weather control	Y	Y	Y	Y	Y	Y

**Figure 2- 2. Comparison of AQI for Wealthy and Less wealthy cities.** *Note: The lower the AQI, the better the air quality.*

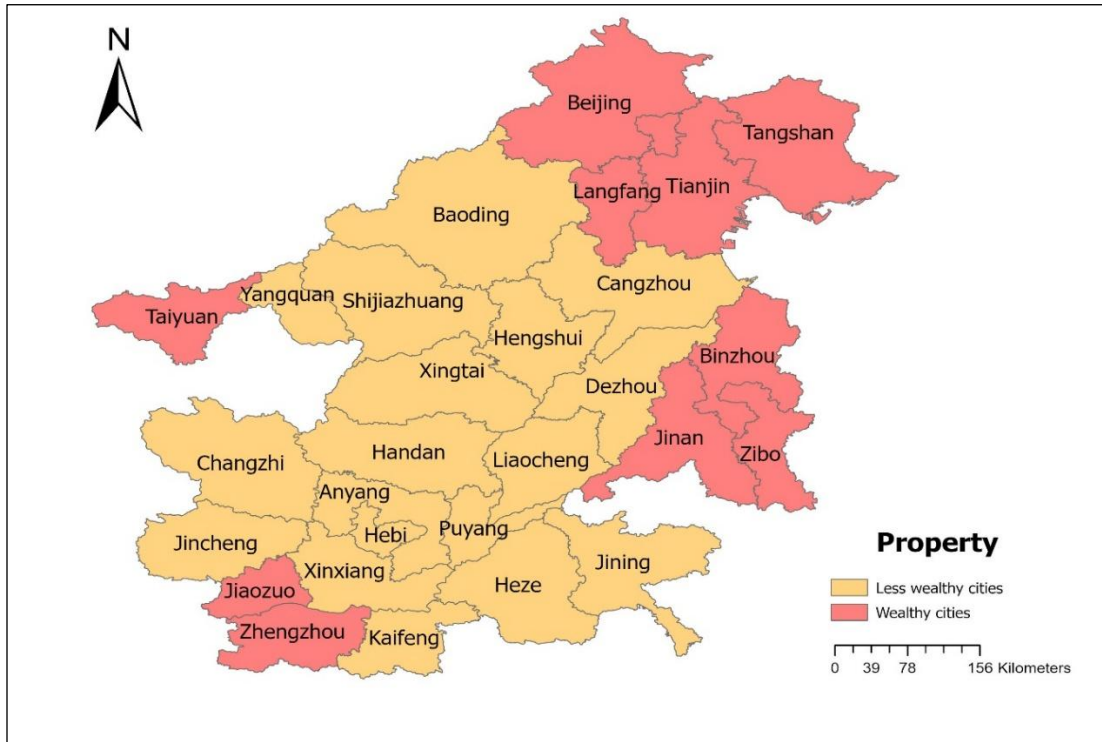


Figure 2-3. Wealthy and less wealthy cities

Based on the threshold model analysis above, the 20 cities (2016-2017 period) are divided into two groups. The first group is the Wealthy group, consisting of Beijing, Jinan, Langfang, Taiyuan, Tangshan, Tianjin, Zhengzhou, Zibo, and Jiaozuo. Newly added to Binzhou during the 2017-2018 action plan. The Less wealthy group included Anyang, Baoding, Cangzhou, Dezhou, Handan, Hebi, Hengshui, Liaocheng, Shijiazhuang, Xinxiang, and Xingtai in the 2016-2017 action plan. After that, the scope is extended to Jining, Jincheng, Kaifeng, Puyang, Yangquan, Changzhi, and Heze (Figure 2-3).

The coefficient of the action plan during the policy period is shown in Table 2-9 and is more remarkable in Wealthy cities than in Less wealthy regions during the 2016-2017 policy period. When the policy was expanded to 28 cities in the 2017-2018 action plan, the reduction coefficients for the Wealthy cities remained higher than those for the Less wealthy regions. During the 2018-2019 policy period, the policy effect in Wealthy cities was significantly

lower than in 2017-2018, while the policy effect in Less wealthy cities increased to -24.60 from -12.84 in 2017-2018. Nonetheless, the data show that Wealthy cities had lower AQI than Less wealthy cities in all three action plans, meaning that air quality was better in Wealthy cities (Figure 2-2).

2.5 Discussion

The article demonstrates the effectiveness of the autumn and winter action plan in improving air pollution through calculations. However, should the scope of the current 28 cities in the Beijing-Tianjin-Hebei region and surrounding area continue to expand, or do we need to further consolidate the policy effect on this basis?

Firstly, in the form of the allocation of emission reduction tasks for autumn and winter action plans. Olson [38] argues that there is such a phenomenon in the whole group and management: Minor leagues are more efficient than major leagues, and mechanical incentives or social pressures only work in minor leagues unless the major league combines minor leagues. The form of task allocation in the autumn and winter action plan is that each city designates different PM_{2.5} emission reduction targets while setting a collective emission reduction target, and such a management mode guarantees significant PM_{2.5} emission reduction.

Secondly, on whether expanding the scope of implementation will improve the overall effectiveness of emission reduction. Diederich [39] points out that when group size becomes more extensive and there is intra-group variability, the expansion of the overall effect comes from individuals who contribute to the group rather than from individuals who are free riders. Likewise, our calculation results indicate that the expansion of the implementation of the autumn and winter action plan from 20 to 28 cities in 2017-2018 compared to 2016-2017 did not result in a significant increase in performance but rather a decrease. This suggests that there are free riders within the 28 cities.

Thirdly, how to minimize free riders. The higher the collective effort [40], the less variability there will be in the level of effort between individuals. That is, the free rider

problem can be solved by continually promoting collective performance. Hence, the improvement in overall emissions reductions in 2019-2020 relative to 2017-2018 helps reduce the variability in the effort put into emissions reductions across cities. Furthermore, the solution [40] to the free rider problem arises because the individual's role in the outcome does not compensate for the costs that the individual can afford. So, this principle also reminds us that we should pay attention to the economic variability among different cities when the policy is implemented.

Fourthly, in the analysis of heterogeneity. Many prior studies have analyzed the heterogeneity of winter-related policies on air pollution. Wang's [37] study classifies cities into mega-cities, medium-sized cities, and small cities and argues that small and medium-sized cities should implement more stringent winter heating-related policies. In Song's article [21], the cities are divided into those that joined initially and later. It is noted that expanding the policy scope brings an increase in policy effects. The study also pointed out that the expansion of the scope of this policy should be based on the maturity of the joint defense and control air pollution system. Tao [41] estimated a reverse U-shaped relation between air pollutant emissions and GDP per capita in China. Ding's study [42] points out that PM_{2.5} and per capita GDP in the Beijing-Tianjin-Hebei region show an inverse U relationship, and the inflection point occurs when the per capita GDP is 129,239 RMB. But in a short time, in the 28 cities in the autumn and winter action plan, only Beijing has achieved a GDP per capita of 129,239 RMB. To further analyze the reasons for amplifying the policy effect, we use Threshold Regression to split 28 cities into two groups: Wealthy and Less Wealthy groups. The article insists that, at this stage, when the city's GDP per capita reaches 65,512 RMB, it will have a structural impact on AQI. When a city's GDP per capita does not reach 65,512 RMB, no structural impacts on AQI occur. At the same time, the data show that the wealthy group has lower AQI than the less wealthy group in all three action plans, meaning that air quality is better in the wealthy group during the action period. In other words, even if the less wealthy group become the main contributors to the policy effects of the action in 2019-2020, air pollution in the less wealthy regions is still worse than in the wealthy regions, and citizens in the less wealthy regions still face more significant health threats than in the wealthy regions.

Therefore, the article suggests that in the autumn-winter action plan, the government should continue to increase the emission reduction target while increasing the economic assistance to less wealthy cities to help them complete the autumn-winter action plan.

2.6 Conclusions and policy implications

The article uses panel data to calculate the effect coefficient of the autumn and winter action plan through RDD regression. The data proves that the autumn and winter action plans for 2016-2017, 2017-2018, and 2019-2020 have improved air quality, with particularly significant reductions in particulate matter. This coincides with the primary goal of the autumn and winter action plan to reduce PM_{2.5} concentrations.

Although the implementation was expanded from 20 to 28 cities in the 2017-2018 action plan, it did not increase overall emission reduction. Meanwhile, the number of cities was maintained at 28 in the 2019-2020 action plan, but the emission reduction effect was increased. This suggests that an increase in the scope of policy implementation does not necessarily lead to an increase in policy effectiveness. Therefore, the article does not recommend expanding the scope of the autumn and winter action plan. Also, considering the improvement in overall emissions reductions in 2019-2020 relative to 2017-2018 helps reduce the variability in the effort put into emissions reductions across cities. The article suggests that the government continues raising emission reduction targets for the autumn and winter programs to solve free rider problems.

To better understand the issue of variability in autumn and winter abatement effects. The article uses a threshold model to divide the cities into the wealthy and less wealthy groups and finds that cities with a per capita GDP of 65,333 RMB (wealthy group) have better air quality than the less wealthy group. Then, the data show that the less wealthy group becomes the main contributor to the policy effects in the 2019-2020 action plan, air pollution in the less wealthy regions is still worse than in the wealthy regions, and citizens in the less wealthy regions still face more significant health threats than in the wealthy regions.

Consequently, less economically developed areas require additional economic support to accelerate industrial transformation and energy structure transition. By recognizing these

disparities and providing targeted assistance, policymakers can foster the desired changes in BHT regions, improving policy outcomes overall.

What's more, the article's areas need further refinement, such as the need for air pollution to consider spatial spillovers between individual cities. The RDD model is suitable for evaluating policies with precise points in time breakpoint. Some of the guidelines in the Autumn and Winter Action Plan, such as optimizing the energy mix, need to be pursued continuously over a long period, and there is no precise time breakpoint. These policies inherently require a more extended time to manifest their intended effects. Therefore, the incorporation of both long-term and short-term periods in policy evaluation is an emerging area of research.

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Supplementary material**Air Quality Index (AQI) Calculation Method:**

The Air Quality Index (AQI) is a composite indicator used to evaluate and communicate air quality levels to the public. In China, AQI is calculated based on six major air pollutants: PM_{2.5}, PM₁₀, SO₂, NO₂, CO, and O₃. The calculation method follows the official technical regulation HJ 633–2012, issued by the Ministry of Environmental Protection (now the Ministry of Ecology and Environment).

For each pollutant, an individual air quality index (IAQI) is calculated using the following formula:

$$IAQI_p = \frac{(I_{Hi} - I_{Lo})}{(BP_{Hi} - BP_{Lo})} \times (C_p - BP_{Lo}) + I_{Lo}$$

Where:

- $IAQI_p$: Individual Air Quality Index for pollutant p
- C_p : Measured concentration of pollutant p
- BP_{Hi} : Breakpoint concentrations closest to but enclosing C_p
- $I_{Hi} I_{Lo}$: AQI values corresponding to $BP_{Hi} BP_{Lo}$
-

After calculating IAQI values for all six pollutants, the final AQI is determined as the maximum of these values:

$$AQI = \max \{IAQI_{PM2.5}, IAQI_{PM10}, IAQI_{SO2}, IAQI_{NO2}, IAQI_{CO}, IAQI_{O3}\}$$

This value reflects the dominant pollutant and indicates the overall level of air pollution at a given time and location.

Chapter 3

QUANTIFYING SOCIO-REGIONAL VARIABILITY VIA FACTOR ANALYSIS OVER CHINA: OPTIMIZING RESIDENTIAL SECTOR EMISSION REDUCTION PATHWAYS

Chapter 3

QUANTIFYING SOCIO-REGIONAL VARIABILITY VIA FACTOR ANALYSIS OVER CHINA: OPTIMIZING RESIDENTIAL SECTOR EMISSION REDUCTION PATHWAYS

3.1 Introduction

The current challenges facing society, as described in the global Sustainable Development Goals (SDGs), specifically good health and well-being (SDG-3) and climate change (SDG-13), necessitate significant changes in energy production, consumer behavior, and policy design [1]. Actions aimed at reducing greenhouse gas (GHG) emissions combat climate change and yield substantial environmental and health benefits, including decreased air pollution. This dual benefit presents policy-makers with an opportunity to amplify the impact of emission reduction strategies [2]. However, to maximize this synergistic effect, policy formulation must consider a range of interconnected factors, such as policy alignment, implementation strategies, and cooperation across different sectors [3]. Policy synergies boost the effectiveness of the various measures. A 2018 study [4] demonstrated that, in Asia, the economic value of climate change mitigation on atmospheric quality and health could reach up to USD 2.8 trillion, with China potentially benefiting from approximately USD 330 billion. Furthermore, shifts in consumer behavior are crucial for the successful implementation of government policies. For example, increased public awareness of environmental conservation and the promotion of low-carbon consumption practices have been reported to contribute to reducing emissions [5]. The national government of China has set targets for peak carbon emissions by 2030 [6] and PM_{2.5} concentrations to be reduced to 35 µg/m³ in most Chinese cities by 2035 [7]. This presents significant challenges in terms of energy production, consumption, and policy design. In a 2022 report, “Synergistic Pathways to Carbon Neutrality and Clean Air in China”, it was proposed that dual goals be

simultaneously pursued: achieving carbon neutrality and improving air quality through synergistic emission reductions in GHG and air pollution (AP). Hence, an increasing number of researchers are investigating methods to better understand the intrinsic link between AP and carbon emissions, assess and validate the efficacy of synergistic management, and devise effective synergistic emission reduction strategies that consider the regional economic and social characteristics of China.

Accordingly, the goal of this study was to provide a country-scale quantitative assessment from which policymakers can optimize synergistic emission reductions of GHG and AP. To that end, 167 articles and reports (the complete list, comprising 167 entries, can be found in Supplementary Materials Table S3-1), which focus on the mechanisms of China's synergistic effects or relevant policies, were selected for review. First, the focus of research from 2019 to 2020 was to determine whether synergistic effects exist between AP and CO₂ emissions [8–15], as well as to analyze synergistic emission reductions in supply chains [16], resource-sharing relationships [17], and the impacts of sulfur dioxide (SO₂) capture technologies on synergistic emission reduction [18]. In 2023, the number of related studies had increased to 56, and the number of topics began to diversify. Researchers have examined how financial development [19–22] and industrial intelligence [23] affect synergistic emissions reductions. Recently, research on synergistic emissions reduction in the industrial [24–28] and transportation sectors [29,30] has emerged. There is also a growing number of studies on the spatial correlation between GHG emissions and AP; for example, the correlation between CO₂ and nitrogen oxides (NO_x) is particularly significant in high-emission regions [31]. The results of a 2023 study [26] indicate that carbon emission reductions have the most significant synergistic effect on SO₂ levels. Other studies have focused on the reasons for spatial variability [32,33], concluding that the synergistic emission reduction effect is significantly better in the eastern region of China than in the western and northern regions in terms of variability across different regions and its relationship with economic structure, energy consumption, and other factors. The number of relevant studies is expected to increase to 80 by the end of 2024. Recently, there has been a focus on synergistic emission reductions in industrial sectors, such as the aluminum industry [34], steel and cement industry [35], coal-

fired industry [36], power generation industry [37,38], industrial sector chain [39], green transformation of heavy industrial agglomerations [40], synergistic estimation of traditional industries [41], and automobile manufacturing supply chain [42]. One research group also focused on the impact of social development progress on synergistic emissions reduction. For example, the impact of the development of digital technology and finance [43–49], such as the impact of high-speed rail openings and the Broadband China strategy [50–53], and the impact of fiscal decentralization on synergistic emissions reduction [54,55], as well as the impact of carbon emissions trading [56–60], have received focus. The impact of the government's disclosure of pollution emissions data on synergistic emissions reduction has also been assessed [61], as well as the impact of the clean development mechanism [62]. In summary, investigators from multiple fields of expertise have explored the impact mechanisms of synergistic emissions reduction from various perspectives.

3.2 Environmental Impact of Public Policy in the Residential Sector

Emissions from the residential sector, although small compared with industrial pollution, are closely linked to residents' health. This indicates that we need to pay attention to emissions from the residential sector and to population health to continuously enhance the effectiveness of government policies. The contribution of residential coal to the total energy consumption decreased further, to 2.9% in 2014, but its contribution to total premature mortality increased to 34% [63]. In 2015, there were 1.1 million premature deaths due to long-term exposure to PM_{2.5}, associated with total household consumption, with urban households accounting for 56% [64].

In the 1950s, the central government introduced a winter heating policy, supplying free coal to the public, but financial constraints restricted this to northern China [65,66]. Consequently, the northern regions began depending on coal for winter heating. To accelerate air pollution reduction and achieve the goals of energy transformation, the Chinese government has implemented a series of ambitious policies. Since 2016, municipalities in the

Beijing–Tianjin–Hebei and neighboring regions, known as the “2 + 26” region, have been annually implementing the Air Pollution Prevention and Control Action Plan (APPCAP, 2013–2017). The primary objectives include improving the air quality during the heating season, reducing PM_{2.5} and other pollutants from coal-fired sources, and promoting cleaner energy use in the Beijing–Tianjin–Hebei region and other key areas. In northern heating areas, “coal-to-gas” and “coal-to-electricity” projects are gradually being promoted to reduce the direct burning of coal [67]. The Three-Year Action Plan for Winning the Battle for the Blue Sky (BSAP, 2018–2020) aims to enhance rural heating methods and ensure that the residents’ demand for electricity for heating is satisfied. It is recommended that the rural “coal to electricity” project be accelerated, power grids upgraded, and facilities be constructed under the “coal to electricity” initiative [68]. In 2021, the Chinese government introduced the 14th Five-Year Plan (2021–2025), which aims to achieve a comprehensive utilization rate of more than 86% for rural straw. In terms of clean energy, the goal is to increase the coverage rate of photovoltaics (PV) on the rooftops of urban public institution buildings and newly constructed factories to 50% by 2025 and increase the rate of renewable energy substitution in urban buildings to 8% [69]. In 2023, the Chinese government proposed a pilot program for rural energy reform; one of the key objectives in 15 pilot counties is to expand the diversification and implementation of renewable energy to exceed 30% by 2025 [70].

Some researchers have focused on the problems that arise during the energy transformation for rural residents. Shen [71] argued that environmental regulations could considerably foster the transformation to clean energy consumption among rural residents, as this can be accomplished through the dissemination of environmental knowledge, technological advancement, and the strengthening of health consciousness among residents. In response to the fact that roughly 172 million rural families in China still depend on traditional biofuels, Yang [72] developed a regional energy model for scenario analysis and discovered that CO₂ emissions could be reduced by 43% if an electrical grid were extensively adopted. Another study [73] recommended that, in rural areas, priority should be given to replacing coal with natural gas, as the use of natural gas boilers for heating can significantly reduce GHG emissions. By 2038, based on the emission reduction targets and

electricity mix, the climate benefits of electricity are projected to be significantly greater than those of natural gas. Zhu et al. [74] demonstrated that rural residential carbon emissions are inversely correlated with the utilization of solar water heaters and biogas digesters and highlighted that renewable energy in rural areas, industrial upgrading, economic growth, and technological innovations significantly influence residential carbon emissions indirectly.

3.3 Research Gap and Framework of Analysis

Exploring the impact mechanism of synergistic emissions reduction is an important research direction. Previous studies on carbon emissions from the rural household sector have concentrated on clean energy transitions, whereas those on particulate matter (PM) emissions from the residential sector have focused on the health damage caused by solid fuels. However, little attention has been paid to whether there is a potential for synergistic emission reduction in the residential sector and whether it can achieve joint reductions in CO₂ and AP. Currently, there is a lack of research on the mechanisms of synergistic emission reduction and the influencing factors.

3.3.1 Objectives of this study

In summary, which provinces and cities should be prioritized for synergistic emission reduction in terms of policy? What local characteristics should be incorporated in the implementation of specific policies? The main goal of this study was to provide an evidence-based approach to answering these questions.

3.3.2 Framework of Analysis

The novelty of this paper lies in its dual-validation approach. This study applies a nested structure combining the coupling coordination degree (CCD) and geographically and temporally weighted regression (GTWR) following the logarithmic mean Divisia index (LMDI) decomposition. This approach extends the decomposition factors and enables

secondary validation. This approach addresses the linkage between the co-reduction mechanism in the residential sector and social factors, enabling the quantification of the co-reduction mechanism and the parameterization of social factors.

The remainder of this article is organized as follows (Figure 3-1): Sections 3.1 and 3.2 provide an overview of the existing research. Sections 3.3 and 3.4 outline our methodology and data sources, respectively. Section 3.5 presents our findings. Section 3.6 discusses the north–south divide and the necessity for coordinated emission reductions in the residential sector, along with suggestions for policy measures. Lastly, Section 3.7 offers a conclusion that encapsulates our key discoveries.

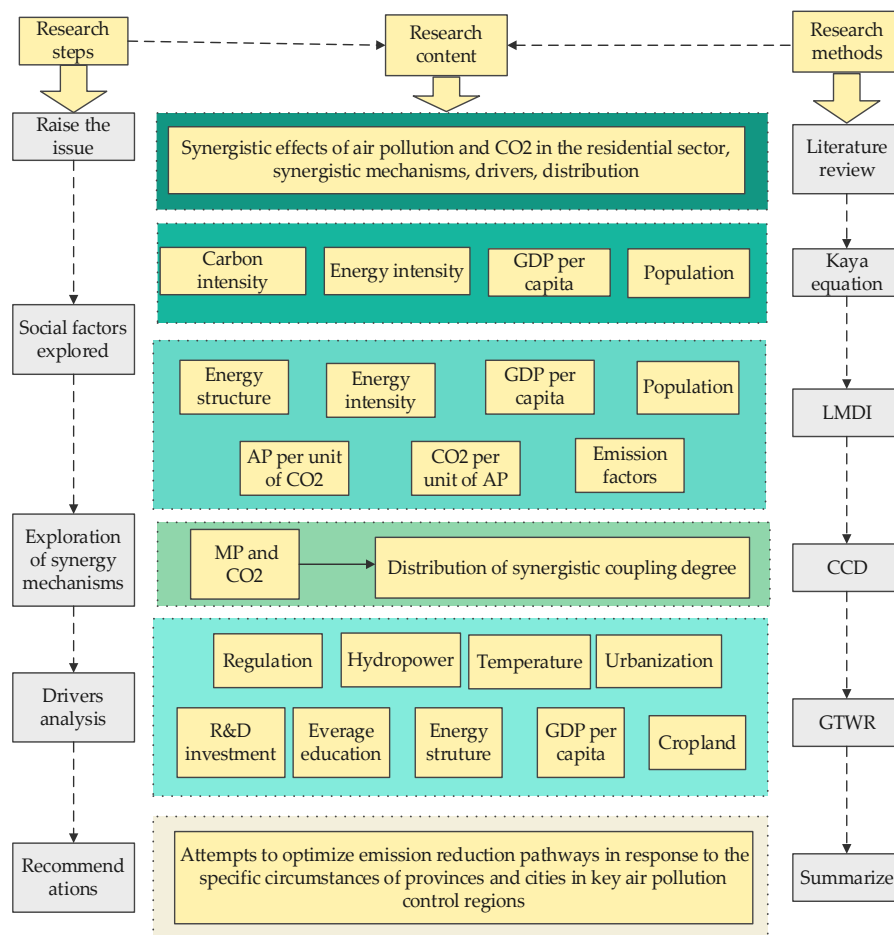


Figure 3-1. Analysis steps and processes.

3.4 Methodology and Data

3.4.1. Decomposition Analysis

$$CO_2 = \frac{CO_2}{Energy} \times \frac{Energy}{GDP} \times \frac{GDP}{Pop} \times Pop \quad (3-1)$$

The Kaya equation [75], which is extensively used worldwide to estimate CO₂ emissions, demonstrates that these emissions are influenced by four key factors: the amount of CO₂ released per unit of energy consumed, energy usage per unit of GDP, GDP per capita, and total population (Pop). This equation establishes the link between carbon emissions and social development indicators. In this study, we extended the Kaya equation to include AP and CO₂ emissions using the logarithmic mean Divisia index (LMDI)—introduced by Ang in 1998 [76]—which has the advantages of the absence of residual terms and ease of interpretation [77]. To comprehend the significance of various factors, decomposition analysis can be employed. There are multiple approaches to accomplish this, including index decomposition analysis (IDA), structural de-composition analysis (SDA), arithmetic mean division index decomposition (AMDI), and logarithmic mean division index decomposition (LMDI). It is worth noting that AMDI contains a residual term [78], while SDA requires more extensive data, specifically input–output tables [79]. In contrast, the LMDI only necessitates time series data for analysis. Contemporary research employs the LMDI to explore concurrent reductions in air pollution and carbon dioxide emissions [8,29,80,81].

$$\begin{aligned} AP &= \frac{AP}{U_{CO_2}} \times \frac{U_{CO_2}}{E_{AP}} \times \frac{E_{AP}}{E_{coal}} \times \frac{E_{coal}}{E_{total}} \times \frac{E_{total}}{G} \times \frac{G}{Pop} \times Pop \\ &= H \times R \times P \times S_t \times S_o \times E \times Z \end{aligned} \quad (3-2)$$

where AP , U_{CO_2} , E_{AP} , E_{gaso} , E_{total} , G , and Pop are the air pollutant concentration, CO₂ emissions, emissions from all types of pollutants, coal usage, total energy consumption in the residential sector, GDP, and population size, respectively. H denotes the AP emissions per unit of CO₂, and R denotes the CO₂ emissions per unit of AP. The combined effects of CO₂

and AP are reflected in H and R . Multiple studies have quantified the combined emission impacts of AP and CO₂ in a comparable manner (Liu & Lin, 2018; Lu et al., 2019; Rive et al., 2010). The emission factors, represented by P , denote the pollutant emissions per coal unit. This is influenced by various factors, including the energy quality utilized by residents, energy combustion efficiency, stove type, and other variables that directly affect emission rates. The proportion of coal in the residential energy consumption is denoted by S_t , which indicates the fuel mix and is associated with an improvement in the fuel structure indicator for the residential sector. The energy intensity of the residential sector is represented by S_o , which measures the energy consumed per unit of GDP. E indicates the GDP per capita, which serves as a marker of economic expansion. Variable Z represents the population, highlighting the effects of the changes in demographic patterns. where AP, U_{co2} , E_{AP} , E_{gaso} , E_{total} , G , and Pop are the air pollutant concentration, CO₂ emissions, emissions from all types of pollutants, coal usage, total energy consumption in the residential sector, GDP, and population size, respectively. H denotes the AP emissions per unit of CO₂, and R denotes the CO₂ emissions per unit of AP. The combined effects of CO₂ and AP are reflected in H and R . Multiple studies have quantified the combined emission impacts of AP and CO₂ in a comparable manner [82–84]. The emission factors, represented by P , denote the pollutant emissions per coal unit. This is influenced by various factors, including the energy quality utilized by residents, energy combustion efficiency, stove type, and other variables that directly affect emission rates. The proportion of coal in the residential energy consumption is denoted by S_t , which indicates the fuel mix and is associated with an improvement in the fuel structure indicator for the residential sector. The energy intensity of the residential sector is represented by S_o , which measures the energy consumed per unit of GDP. E indicates the GDP per capita, which serves as a marker of economic expansion. Variable Z represents the population, highlighting the effects of the changes in demographic patterns.

Using the LMDI method, this study calculates the yearly variations in pollutant levels (ΔAP). The starting year is denoted by o and the ending year by t . The variables ΔH , ΔR , ΔP , ΔS_o , ΔS_t , ΔE , and ΔZ represent the contribution rates of each factor from the starting to the ending year. These factors correspond to the contribution rate of AP per unit of CO₂, CO₂

per unit of AP, energy structure in the residential sector, emission intensity in the residential sector, GDP per capita, and population size.

$$\begin{aligned}
 \Delta AP &= AP^t - AP^o = \Delta H + \Delta R + \Delta P + \Delta S_o + \Delta S_t + \Delta E + \Delta Z \\
 &= \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{H^t}{H^o} \right) + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{R^t}{R^o} \right) \\
 &\quad + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{P^t}{P^o} \right) + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{S_o^t}{S_o^o} \right) \\
 &\quad + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{S_t^t}{S_t^o} \right) + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{E^t}{E^o} \right) \\
 &\quad + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{Z^t}{Z^o} \right)
 \end{aligned} \tag{3-3}$$

3.4.2. Coupling Coordination Degree (CCD)

Based on the characteristics of pollutants and GHG from the residential sector, this study used the total amounts of CO₂ and particulate matter (PM_{2.5}, PM₁₀, OC, and BC) to construct a coupled model using the following equations:

$$C = \sqrt{\frac{X \times Y}{(X + Y)^2}} \tag{3-4}$$

$$T = \alpha X + \beta Y \tag{3-5}$$

$$D = \sqrt{C \times T} \tag{3-6}$$

where C is the degree of coupling, X is the total CO₂ emissions from the residential sector, Y is the total particulate matter (PM) emissions from the residential sector, and T is the combined evaluation index of CO₂ and PM emissions. As both are equally important, α and

β are the coefficients of the carbon emissions and particulate matter and are taken to be 0.5, considered that they are both equally important. D is the degree of compatibility between the carbon emissions of the residential sector and particulate matter, which is used as a measure of the strength of the interactions. It is a neutral measure and does not inherently reflect a positive or negative judgment.

3.4.3. Geographically and Temporally Weighted Regression (GTWR)

The hidden causal relationships between the factors cannot be decomposed using Kaya's equation. To identify the real drivers of pollutant emissions, it is necessary to analyze the causal relationships among the Kaya equation factors and their respective subcomponents [85,86]; that is, the compounding effect among these factors is not reflected in the decomposition of the LMDI, which may lead to underestimation or overestimation of the factor's contribution [87]. Therefore, the GTWR model was adopted to solve the issue of factor covariance. Compared with the common geographically weighted regression (GWR), which uses cross-sectional data, the GTWR model can incorporate panel data from 2001 to 2020, thereby improving estimation accuracy. The coupling coordination degree (CCD) calculated by the CCD model serves as the dependent variable in GTWR, while GTWR captures the spatial-temporal relationships of various factors with CCD.

$$Q_i = \delta_o(\mu_i, v_i, t_i) + \sum_{j=1}^n \beta_j(\mu_i, v_i, t_i) L_{tij} + \varepsilon_{ti} \quad (3-7)$$

$$\hat{\beta}(\mu_i, v_i, t_i) = [X^T M(\mu_i, v_i, t_i) X]^{-1} X^T M(\mu_i, v_i, t_i) Y \quad (3-8)$$

In this equation, Q_i is the dependent variable, and n represents the total number of provinces. The independent variables are denoted as L_{tij} , δ_o stands for the intercept, and β_j symbolizes the regression coefficient. The error term is represented by ε_{ti} . The matrix $M(\mu_i, v_i, t_i) = \text{diag}(\alpha_{i1}, \alpha_{i2}, \dots, \alpha_{in})$ is defined, where α_{ij} represents the spatiotemporal

distance functions corresponding to the weights employed when adjusting for weighted regressions adjacent to province *i*.

3.4.4. Study Area and Data

Panel data covering the years 2001 to 2020 were collected from 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan; the 30 provinces include four municipalities directly under the central government: Beijing, Tianjin, Shanghai, and Chongqing). Air pollutants included SO₂, NO_x, CO, VOC, NH₃, PM₁₀, PM_{2.5}, black carbon, organic carbon, and CO₂ from 2001 to 2020, as obtained from the MEIC [88,89] model (Table S3-2 in the Supplementary Materials). Population, GDP, and the ratio of the urban population for 2001–2020 were obtained from the China Statistical Yearbook. Data on the total energy consumption and total coal consumption in the residential sector from 2001 to 2020 were derived from the China Energy Statistical Yearbook. Specifically, coal consumption and total energy consumption were calculated using the conversion tables provided in the China Energy Statistical Yearbook 2020. The specific conversion coefficients were as follows: firewood at 0.571 kg of standard coal per kilogram, straw at 0.486 kg of standard coal per kilogram, and biogas at 0.714 kg of standard coal per cubic meter. Investment data for industrial pollution control were obtained from the China Environmental Statistical Yearbook. Electricity consumption by province and hydropower generation data were obtained from 2001 to 2020 were obtained the China Energy Statistics Yearbook and provincial statistical yearbooks. Data on the average years of education from 2001 to 2020 were obtained the China Statistical Yearbook, China Population Yearbook, and Employment Statistical Yearbook. Data on research and development expenditures (R&D investment) from 2001 to 2020 were obtained from the China Science and Technology Statistical Yearbook. The annual average temperatures of the provinces were calculated for 2001–2020 from the monthly average temperatures in the ERA5-Land dataset published by the European Union and the European Center for Medium-Range Weather Forecasts, Copernicus Climate Data Store (CDS, <https://cds.climate.copernicus.eu/datasets?q=ERA5-Land>).

The Qinling–Huaihe Line starts west of the Qinling Mountains (E 104°15, N 31°18) and ends at the seashore of the East China Sea (E 120°21, N 34°05) [90]. The Qinling–Huaihe Line is widely acknowledged as the dividing line between the northern and southern regions of China in terms of its significant climatic, ecological, and economic distinctions [91–93]. The four geographic regions used in this study are as follows (Figure 3-2): North China: Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, Shandong, Henan, Shaanxi, Ningxia, Xinjiang, and Qinghai. South China: Shanghai, Zhejiang, Jiangsu, Anhui, Fujian, Jiangxi, Hunan, Hubei, Guangdong, Guangxi, Hainan, Sichuan, Chongqing, Guizhou, Yunnan, and Tibet. The Beijing–Tianjin–Hebei region (BTH) includes Beijing, Tianjin, Hebei, and the neighboring provinces of Shanxi, Shandong, and Henan. The Yangtze River Delta (YRD) region includes the provinces of Shanghai, Jiangsu, Zhejiang, Anhui, Jiangsu, and Anhui.

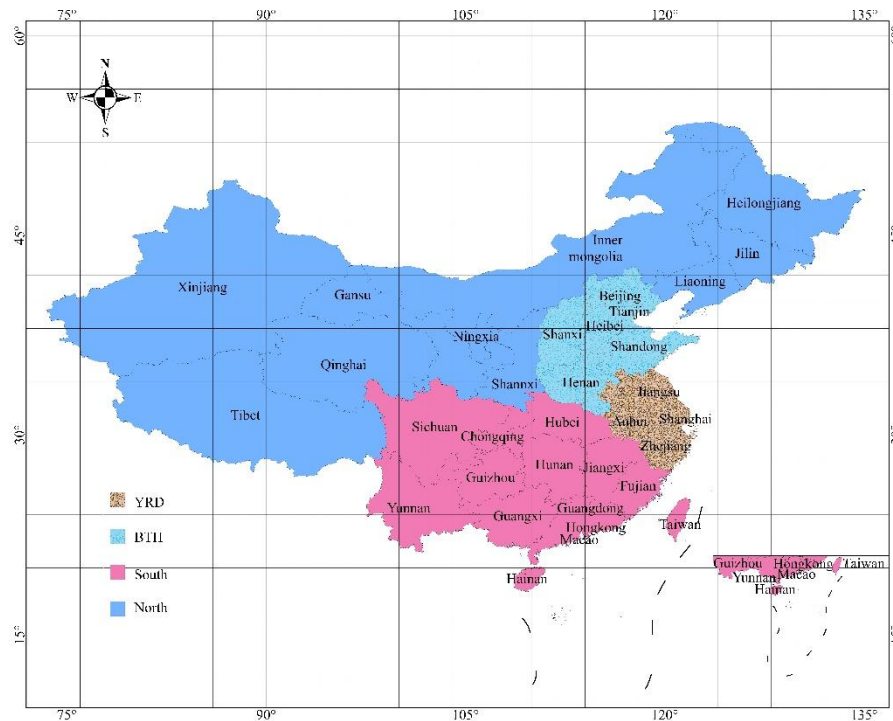


Figure 3-2. Geographic divisions for the purpose of this study.

3.5. Results

3.5.1. Overview of Total Emissions

The emission rates of AP and CO₂ from the residential sector exhibited an overall decrease (Figure 3-3), particularly post-2013, with negative growth except for NH₃. The CO₂ levels did not decrease, and CO₂ represented a growing proportion (as much as 80%) of the total residential emissions (Figure 3-4d). The 30 provinces and cities were categorized into northern and southern regions based on the Qinling–Huaihe River Line. The data indicate that air pollutant emissions from residential areas in the south have consistently exceeded those from the northern regions, and this disparity has gradually widened since 2015. CO₂ emissions were higher in the northern regions; However, post-2015, emissions in the north declined. In contrast, in residential areas in the southern regions, emissions maintained the same growth trajectory, leading to a reduction in the disparity between the two regions. Furthermore, as shown in Figure 3-5, the disparity in emissions between the north and south continued to increase from 2016 to 2020. A significant portion of pollutant emissions from residential areas stems from coal consumption (Figure 3-4, a–c); pollution from coal consumption accounts for 70–57% (average of 30 provinces) of residential emissions.

In 2020, 50% of the pollutant emissions (AP and CO₂) from the residential sector (Figure 3-5) in the north stemmed from coal combustion, compared with 30% of emissions in the south, indicating that northern residents are more dependent on coal for fuel use. Specifically, pollution sources in the northern region exhibited significant regional variations; for example, residential emissions (AP and CO₂) constituted over 70% of the emissions in Beijing and Tianjin but only 57% in Hebei (Figure 3-6). In Shanxi, Inner Mongolia, Liaoning, Jilin, Heilongjiang, and Xinjiang, coal use accounted for 76%, 90%, 64%, 77%, 87%, and 78% of the total emissions, respectively (Figure 3-6). Tibet is an exception, with 98% of the air-borne pollution emanating from biofuel combustion (Figure 3-6). In the south, a very large proportion of emissions were attributed to coal use: 71% in Hubei, 83% in Hunan, 94% in Guizhou, and 81% in Yunnan. In Shanghai, Zhejiang, Jiangsu, and Guangdong, the

residential sources accounted for 98%, 89%, 81%, and 86% of the total pollutant emissions, respectively (Figure 3-6). Regarding the total emissions of AP and CO₂, Guizhou ranked first, Heilongjiang second, and Hunan third (Figure 3-7). In these three provinces, 80% of the pollution is attributed to coal use (Figure 3-6). Notably, Guizhou and Hunan are part of the southern region. In conclusion, pollution emissions from coal use were higher in the northern region than in the southern region. Of the 30 provinces and cities, 12 had more than 50% of their residential pollution emissions stemming from coal use, and 17 had more than 50% from other residential sources, indicating that, beyond the use of coal and biomass fuels, other daily activities of residents are also a significant source of pollution. Regarding regional distribution, pollution sources have deviated significantly from the traditional north–south zoning pattern.

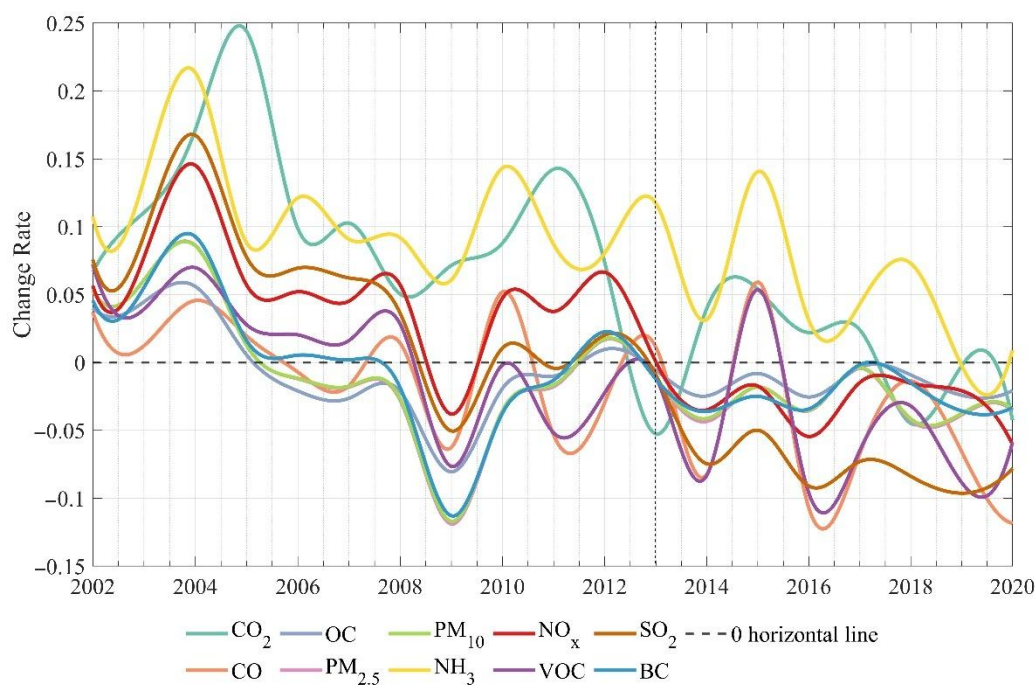


Figure 3-3. Rates of change in pollutant emissions. *Note: vertical dotted lines indicate 2013.*

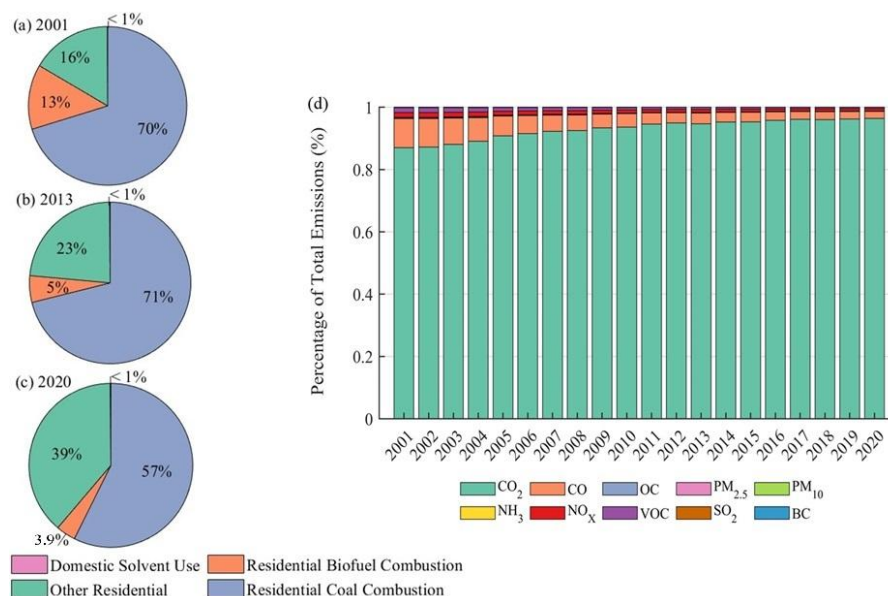


Figure 3-4. Changes in the relative contribution of sources and types of pollutants. *Note:* The subfigures (a)–(c) show the variations in the contribution of emission sources from the residential sector, while (d) presents the changes in the proportion of different pollutants.

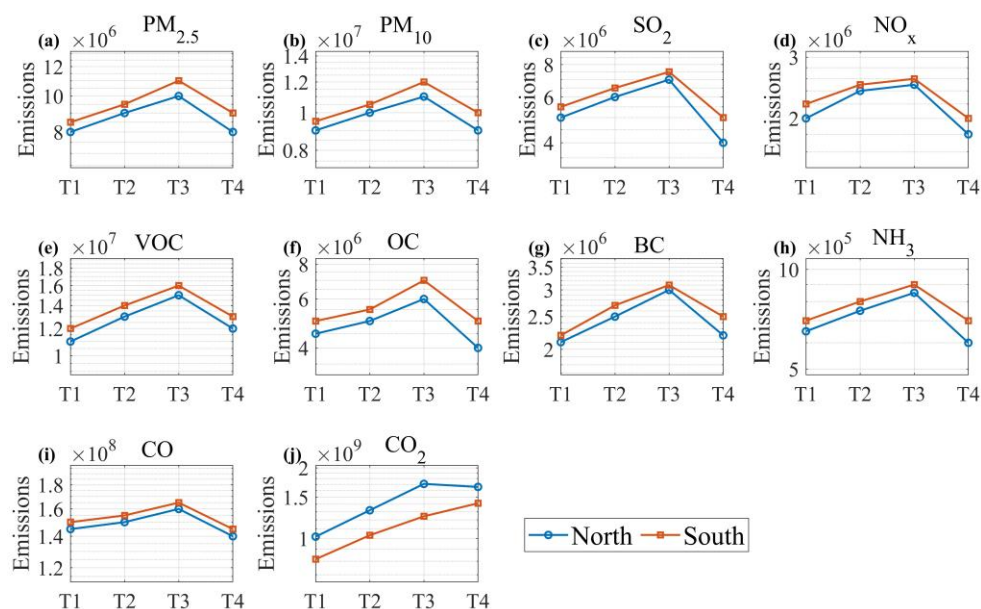


Figure 3-5. North–South comparison of North–South emissions. *Note:* T1, 2001–2005; T2, 2006–2010; T3, 2011–2015; and T4, 2016–2020. The subfigures (a–j) show sources of PM_{2.5}, PM₁₀, SO₂, NO_x, VOC, OC, BC, NH₃, CO, CO₂, separately. Emissions measured in tons.

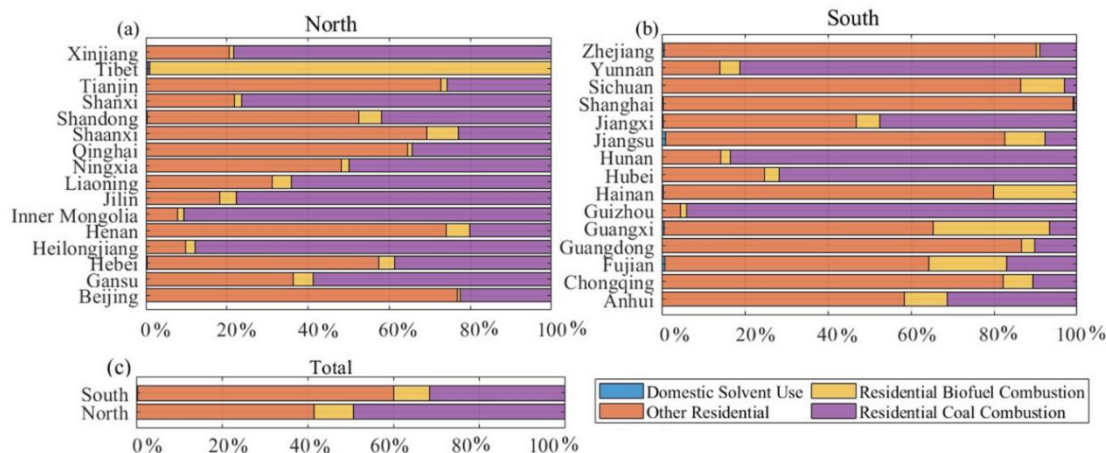


Figure 3-6. North–South comparison of pollution sources. *Note: Subfigures (a)–(c) illustrate the proportion of pollution sources in northern regions in 2020, southern regions in 2020, and a comparison of the average values between the north and south, respectively.*

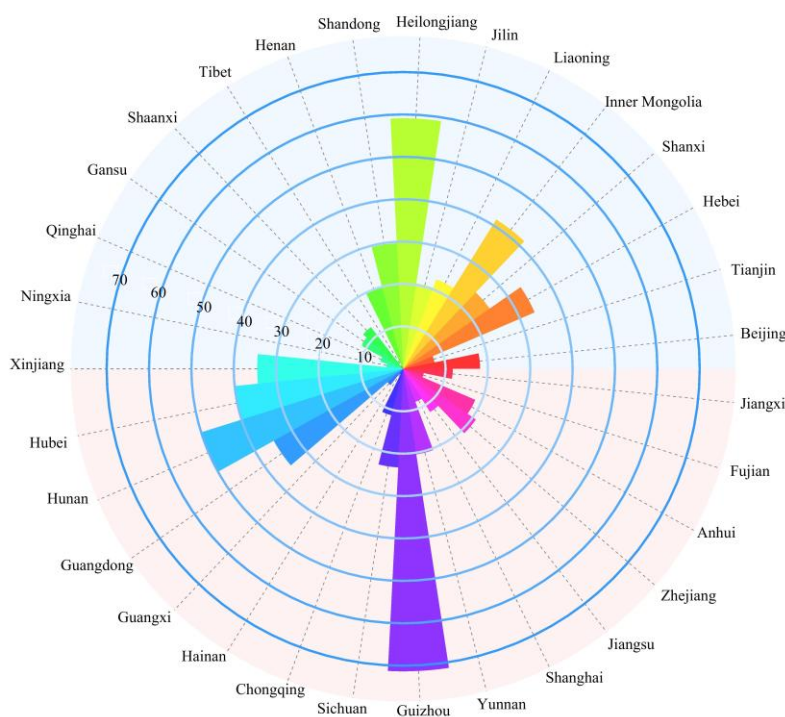


Figure 3-7. Emissions of provinces and cities in 2020. *Note: areas in the north are colored blue and those in the south pink. The petals of the rose chart represent the combined emissions of air pollutants and CO₂, with different petal colors indicating the emission levels of various provinces and cities.*

3.5.2. Air Pollution Emission Factors and Regional Differences

To understand the social factors influencing emissions in the residential sector, this paper analyzes and compares the contributions of various social factors to emissions while also examining regional disparities.

Table 3-1. Overall effect of factors on pollution emissions.

Factor	PM _{2.5}	PM ₁₀	SO ₂	VOC	NO _x	CO	OC	BC	NH ₃
H	-0.361	-0.373	-0.226	-0.470	-0.056	-4.746	-0.226	-0.057	-0.043
R	26,348	31,541,165	-0.0079	2393.2	9003.6	914.2	46,972	113,092	-5671
P	323,343	322,495	211,847	658,966	75,452	4,261,807	211,847	46,413	67,967
St	-4.748	-4.748	-4.748	-4.748	-4.748	-4.748	-4.748	-4.748	-4.748
So	-5.246	-5.246	-5.246	-5.246	-5.246	-5.246	-5.246	-5.246	-5.246
E	8.440	8.440	8.440	8.440	8.440	8.440	8.440	8.440	8.440
Z	14,331	14,331	14,331	14,331	14,331	14,331	14,331	14,331	14,331

Note: H, AP emissions per unit of CO₂; R, CO₂ emissions per unit of AP; P, emission factor; S_t, energy structure; S_o, emission intensity; E, GDP per capita; Z, population. (Regardless of which pollutant corresponds to the emission structure of the residential sector, the emission intensity, GDP per capita, and population in the same area make the same contributions. The average P is 686,681.9).

In the residential sector, the CO₂ emissions were significantly higher than the AP emissions, resulting in low H values (Table 3-1 the LMDI decomposition results are unitless) and high C values (except for SO₂ and NH₃). Consequently, the emissions of CO₂ per unit of air pollutant (R) are a substantial contributor to the overall pollution emissions. Energy structure (S_t) and intensity (S_o) exert an inhibitory effect on pollutant emissions. However, this effect is minor, with air pollutant emissions being more significantly influenced by population size (Table 3-1, Z value) than by GDP per capita (Table 3-1, E value). In

conclusion, the energy emission factor (P) and population (Z) contribute significantly to pollutant emissions and represent the primary focus of future emission reduction efforts. In particular, the goal should be to reduce the energy emission factor through energy substitution or upgrading residential energy use, as well as prioritize emission reductions in provinces and cities with large population bases, taking into consideration population distribution characteristics. In addition to reducing NH_3 and other pollutants, synergistic emission reduction possibilities (H+R) exist. However, to date, no such synergistic emission reduction has been achieved.

Z contributed to pollutant emissions in both the south and north and the value of Z gradually decreased in the north while it increased in the south (Figure 3-8). Notably, after 2015, the Z-values (Table 3-2) were significantly higher in the south than in the north, indicating that planning the residential sector to reduce emissions based on population distribution is more effective in the southern regions. The synergistic effect of AP and CO_2 (H+R) increased in both the south and north, and the magnitude of the increase in the south was significantly higher than that in the northern region. Particularly after 2015, the R-value (Table 3-2) was considerably higher in the southern region than in the northern region. This indicates that the contribution of AP due to the increase in CO_2 emissions in the south after 2015 was much larger than that in the north. Additionally, P transitioned from a reducing effect to a facilitating effect, and in terms of the emissions of particulate matter other than $\text{PM}_{2.5}$, the value of P in the southern provinces and municipalities was significantly higher than that in the northern region. These findings suggest that the emission factors in the southern region play a significant role in pollutant emissions. Given that population size has a greater impact on the southern region, it is advisable to prioritize the implementation of energy upgrading and replacement policies in the southern region, where there are larger population centers. This approach is likely to be more effective at reducing pollutant emissions.

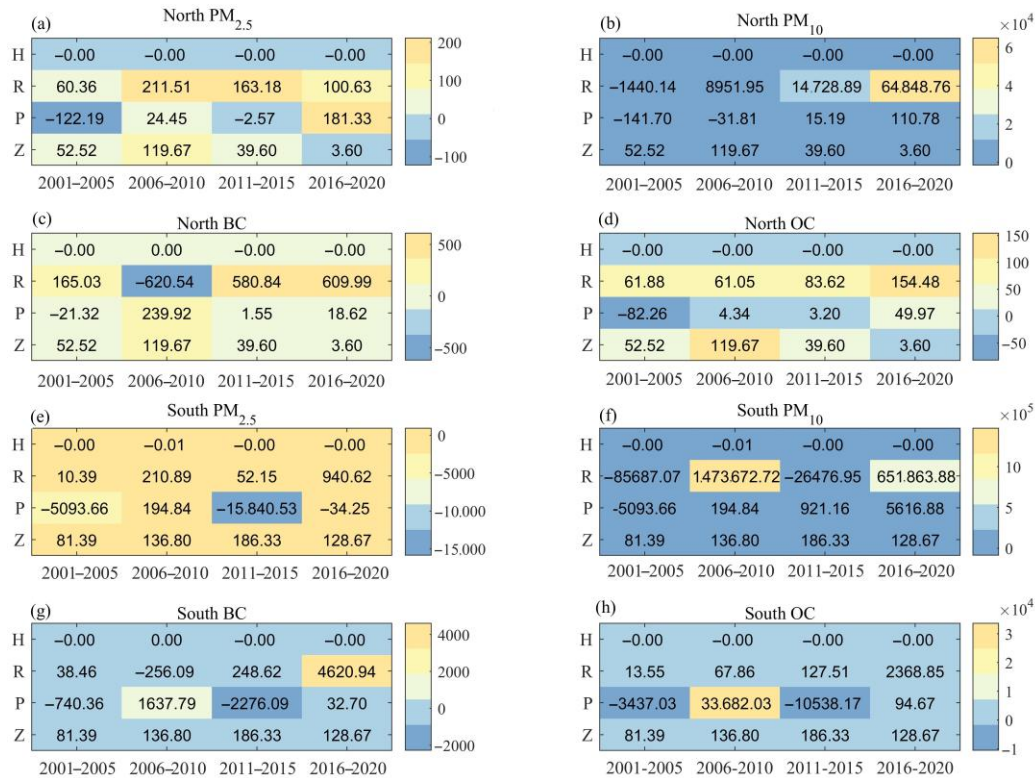


Figure 3-8. North—south emission driving factors. *Note: H, AP emissions per unit of CO₂; R, CO₂ emissions per unit of AP; P, emission factor; Z, population. Numbers indicate the role of the H, R, P, and Z factors in emissions. South and north represent the averages of the north and south provinces, respectively. Subfigures (a)–(d) illustrate the contribution of the four factors to PM_{2.5}, PM₁₀, BC, and OC emissions in northern regions, while subfigures (e)–(h) present the contributions of these factors to the same pollutants in southern regions.*

Table 3-2. Comparison of north and south drivers.

North			South		
PM _{2.5}	2011–2015	2016–2020	PM _{2.5}	2011–2015	2016–2020
R	163.175	100.634	R	52.145	940.619
Z	39.600	3.600	Z	186.333	128.667
BC	2011–2015	2016–2020	BC	2011–2015	2016–2020
R	580.840	609.986	R	248.624	4620.941
Z	39.600	3.600	Z	186.333	128.667
PM ₁₀	2011–2015	2016–2020	PM ₁₀	2011–2015	2016–2020
R	14,728.893	64,848.763	R	-26,476.948	651,863.882
Z	39.600	3.600	Z	186.333	128.667
OC	2011–2015	2016–2020	OC	2011–2015	2016–2020
R	83.618	154.480	R	127.510	2368.854
Z	39.600	3.600	Z	186.333	128.667

As discussed in Section 3.5.1, the spatial distribution of pollution sources from the residential sector has shifted away from the traditional north–south division. To better analyze the spatial distribution of the promoting effects of social factors on emissions, we have grouped the LMDI decomposition results using radar charts. Figure 3-9 illustrates (detailed data in Table 3-3) that the contribution of seven factors to PM_{2.5} emissions in 30 provinces indicates that these provinces could be divided into four types. The first type is characterized by a high population factor (Z), which significantly influences emissions. In the provinces of Beijing, Tianjin, Hebei, Shanxi, Henan, Shandong, Shaanxi, Zhejiang, Jiangxi, Guangdong, and Yunnan, urban planners should address the high residential emissions stemming from large populations. The second type comprises provinces with a high R-value (CO₂ emissions per unit of AP), signifying an imbalance between AP and CO₂. This category includes Liaoning, Gansu, Ningxia, Qinghai, Xinjiang, Shanghai, Hubei, and Hunan provinces. The third category includes provinces with high-emission factors (P), necessitating improvements in residential energy structures and stoves to reduce emissions. This group included Hainan, Guizhou, Sichuan, Yunnan, Chongqing, Guangxi, Jiangsu,

Fujian, and Anhui. The fourth type, referred to as the mixed type, includes Jilin, Inner Mongolia, and Heilongjiang.

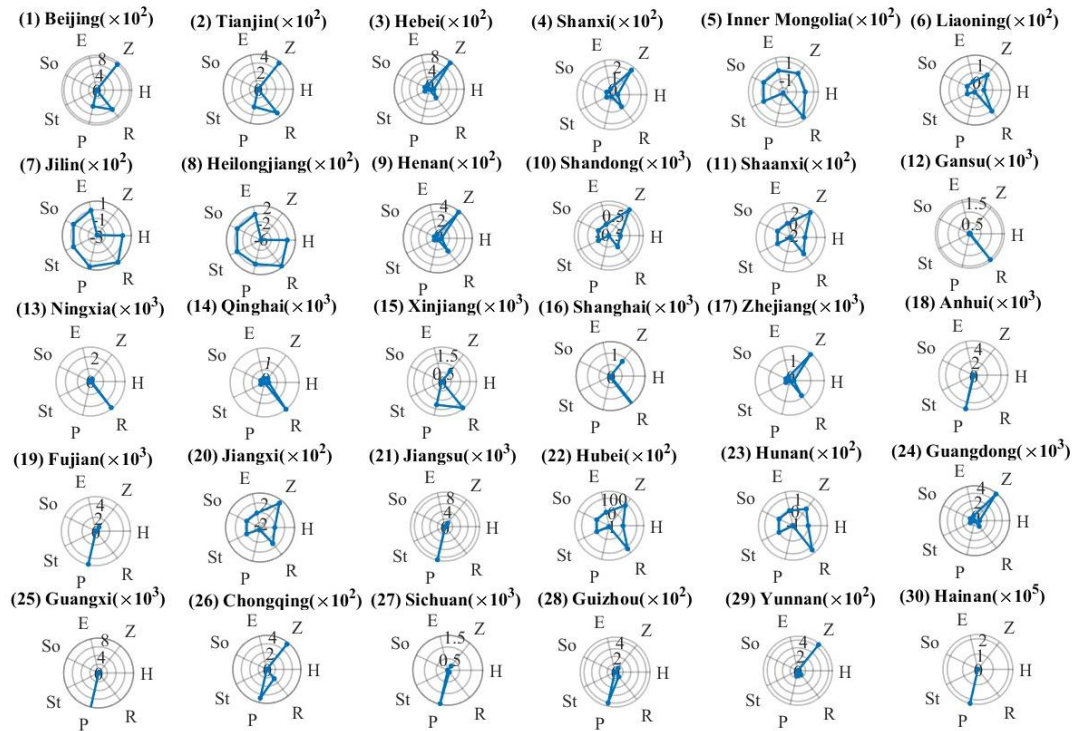


Figure 3-9. Contribution of seven factors to PM_{2.5} emissions in 30 provinces. *Note: This visually represents the contribution of seven factors to PM_{2.5} emissions across 30 provinces, with each province's contributions depicted by specific numerical values within concentric circles. For instance, Beijing's contributions are indicated by the second concentric circle with a value of 4×10^2 and the fourth circle with 8×10^2 . This graphical representation allows for a clear distinction between the northern provinces, labeled (1)–(15), and the southern provinces, labeled (16)–(30). For detailed data, please refer to section 3-4 and Table 3-6.*

Table 3-3. Contributions of seven factors to PM_{2.5} emissions in 30 provinces and cities.

Provinces	H	R	P	St	So	E	Z
Beijing	-0.004	604.357	404.72	-0.096	-0.29	0.4	803.9
Tianjin	-0.004	348.203	208.57	-0.399	0.137	0.03	383
Hebei	-0.007	165.005	-120.86	-0.195	-0.23	0.31	765
Shanxi	-0.002	81.6693	-31.263	0.007	-0.54	0.46	218
Inner Mongolia	-0.008	117.515	-235.76	-0.061	0.405	0.19	22
Liaoning	-0.008	104.136	-38.328	-0.122	-0.02	0.21	61
Jilin	-0.008	95.8206	70.421	-0.043	-0.04	0.6	-292
Heilongjiang	-0.024	165.642	-45.771	0.0909	0.027	0.2	-640
Shanghai	-0.002	14,144.9	60.742	-0.222	-0.02	-0.07	820
Jiangsu	-0.026	131.055	8884.9	-0.38	0.061	0.48	1118
Zhejiang	-0.013	875.27	-241.66	-0.194	0.056	0.21	1739
Anhui	-0.015	78.2253	4995.3	-0.422	-0.13	0.34	-23
Fujian	-0.02	34.9387	4923.7	-0.384	-0.01	0.32	716
Jiangxi	-0.015	116.177	-256.37	-0.225	0.053	0.27	333.2
Shandong	-0.011	151.479	-597.12	-0.123	0.078	0.29	1124
Henan	-0.009	161.376	-36.367	-0.217	-0.22	0.28	386
Hubei	-0.014	114.77	-93.201	-0.125	-0.05	0.5	87
Hunan	-0.016	122.36	-118.92	-0.167	0.12	0.33	49
Guangdong	-0.008	318.022	-612.98	-0.047	0.104	0.05	3891
Guangxi	-0.053	29.7003	75,691	-0.068	-0.03	0.31	231
Hainan	-0.038	50.8831	227,557	-0.013	0.058	0.23	216.4
Chongqing	-0.011	138.719	346.41	-0.482	0.04	0.23	379.8
Sichuan	-0.017	104.727	1470.7	-0.373	-0.12	0.3	228
Guizhou	-0.005	72.3741	408.32	-0.023	-2.25	0.31	59
Yunnan	-0.008	62.7833	65.636	-0.136	-0.24	0.33	434.6
Shaanxi	-0.01	115.349	-248.22	-0.104	-0.03	0.4	302
Gansu	-0.002	1535.84	-15.243	-0.11	-0.22	0.18	-22
Qinghai	-0.001	1790.11	-235.44	-0.126	-0.41	0.25	69.9
Ningxia	-0.002	2710.94	-94.372	0.0452	-0.77	0.35	158
Xinjiang	-0.002	1806.49	1278.1	-0.034	-0.78	0.16	714

Note: The LMDI decomposition results are unitless. In the BHT (Beijing, Tianjin, Hebei, Shanxi, Shandong, and Henan) regions, Z averages 613.

3.5.3. North–South Coupling Coordination Degree

We investigated the coordinated coupling of particulate matter (PM) and CO₂ across 30 provinces and cities and examined the dynamics of coordinated emissions reduction in the residential sector. The findings showed a slight decrease in coordinated coupling, from 0.228 in 2001 to 0.220 in 2020. However, this change was not significant, and the overall state remained at moderate dysregulation (Table S3-3 in the Supplementary Materials). Emissions from the residential sector showed minimal synchronization between the PM and CO₂ levels. Although progress has been made in one area, the regulatory impact on another remains minimal, potentially leading to an imbalanced effectiveness of emission reduction strategies. The average coupling value in the northern provinces and cities was 0.239, whereas it was 0.224 in the southern provinces and cities. This suggests a significantly higher average coupling in the northern regions than in the southern regions. Among the 30 provinces examined, ten showed an upward trend: Hubei, Hunan, Fujian, Heilongjiang, Anhui, Guangxi, Hainan, Sichuan, Yunnan, and Shaanxi. The mean coupling value for these ten provinces increased from 0.205 in 2001 to 0.239 in 2020.

3.5.4. Drivers of Coupling Coordination Degree

To further explore the mechanisms of synergistic emission reduction in the residential sector, we employed the GTWR model to analyze the driving factors. The variable selection process was carried out in two stages: Initial Screening: Variables were initially drawn from two sources. First, we included key factors from the LMDI model, such as the residential sector emissions factor, energy composition, energy efficiency, GDP per capita, and population size. Second, we incorporated additional factors that are commonly examined in emission-related studies, such as income disparity [94], environmental regulation [28], the digital economy [95], population density [96], average years of education [97], years of tertiary education [97], urbanization rate [98], NDVI [99], and R&D investment [74]. Final Selection: To avoid multicollinearity, all variables underwent a variance inflation factor (VIF) test (Table 3-4). Based on this test, the following variables were selected: GDP per

capita, hydroelectricity generation, environmental regulation, population size, temperature, urbanization rate, average years of education, R&D investment, and electricity consumption (Table 3-5). The GTWR model constructed with these variables demonstrated strong performance, achieving an adjusted R^2 of 0.885 and the lowest AICc value among the tested models (Table 3-6).

Table 3-4. VIF test.

Variable	VIF	1/VIF
Everage education	4.75	0.210596
GDP per capita	4.03	0.24803
R&D investment	4.02	0.248718
Urbanization	3.44	0.290978
Cropland	2.42	0.412516
Temperature	1.82	0.548412
Regulation	1.23	0.816154
Energy structure	1.15	0.871267
Hydropower	1.14	0.877559
Mean VIF	2.67	

Table 3-5. Statistical description.

Variable	Sample	Unite	Mean	Min	Max	Std. Dev.
CCD	600	—	0.23139	0	0.25	0.033472
RD investment	600	%	0.013976	0.001514	0.064444	0.010801
Regulation	600	%	0.004379	0.000085	0.030988	0.003758
Everage education year	600	year	8.664195	6.04047	12.782	1.059097
Energy structure	600	%	0.033317	0.0029	0.1097	0.023423
Hydropower	599	%	256.5179	0	3541.38	491.7662
GDP per capita	600	CNY	10,257.26	2743.874	29,039.82	5501.658
Cropland	600	ha	1059.427	42.69406	5417.912	896.716
Temperature	600	°C	12.41496	-4.0224	25.07904	6.002517
Urbanization	600	%	0.517295	0.1389	0.896	0.155166

Table 3-6. Comparison of regression results.

Model	R²	Adjusted R²	AICc	Bandwidth
OLS	0.279	—	1525.791	—
GWR	0.768	0.764	983.535	0.115
GTWR	0.887	0.885	720.642	0.115

Figure 3-10, a–i presents the spatial distribution of the regression results from the GWTR model, reflecting the influence of the selected social factors on CCD in each province and city. A positive coefficient indicates promotion, while a negative coefficient indicates weakening. Figure 3-10, a–i corresponds to the following social factors: R&D investment, environmental regulation, average years of education, energy structure, GDP per capita, per capita cropland, hydroelectricity generation, temperature, and urbanization. For detailed coefficients for each province and city, please refer to Table 3-7.

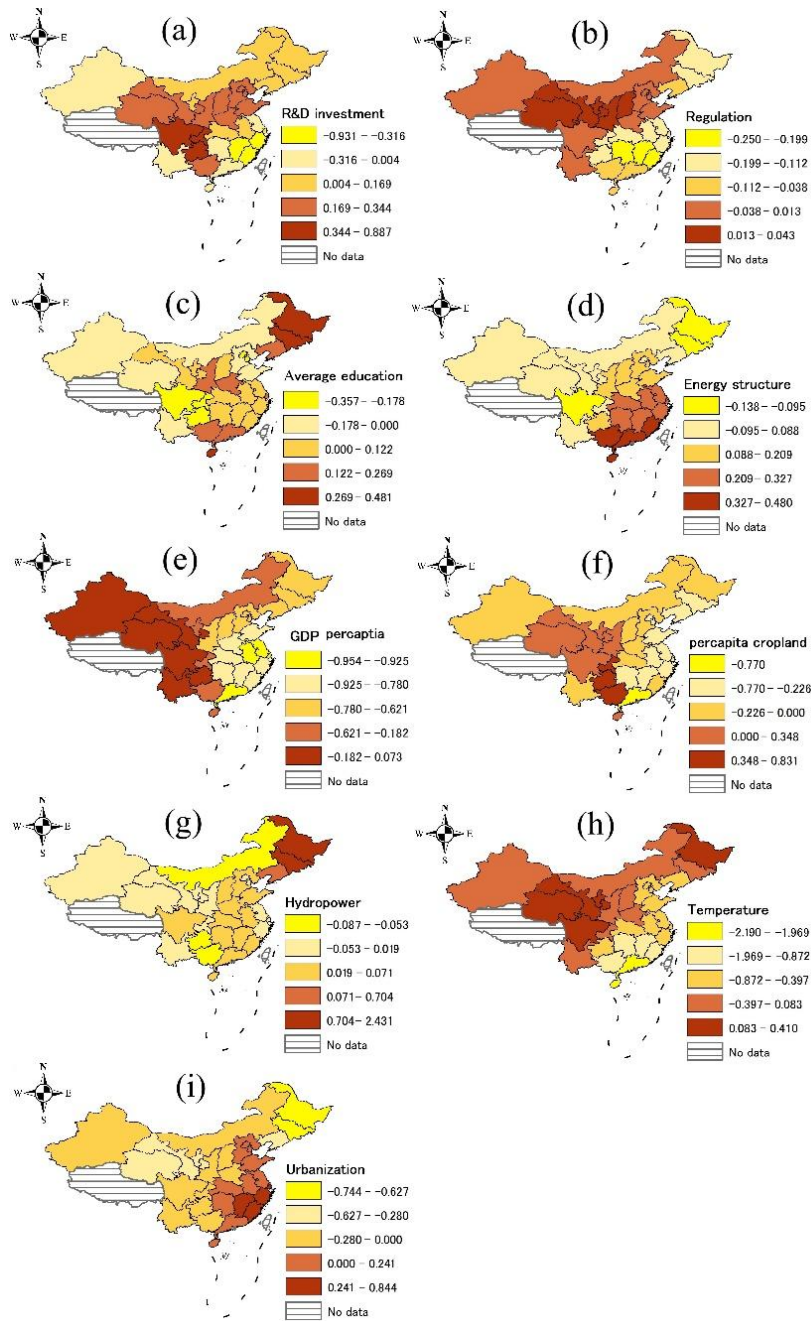


Figure 3-10. Distribution diagram of factors driving the degree of coupling based on averages in the period of 2001–2020. *Note: Regression coefficients with p -values > 0.1 are excluded. The legend illustrates each factor's coefficient of influence on the coupling degree, where positive values indicate a promoting effect and negative values suggest a weakening impact. Subfigures (a)–(i) respectively depict the spatial distribution of the impact*

coefficients of R&D investment, environmental regulation, average years of education, energy structure, GDP per capita, per capita cropland, hydroelectricity generation, temperature, and urbanization on CCD.

The share of research and development expenditures (R&D investment) in GDP indicates the level of importance that a region assigns to innovation and affects the emissions of the residential sector [74]. As Figure 3-10a shows, an increase in the share of R&D investment exerts both positive and negative effects on coordination coupling across different regions. Weakening effects were evident in 7 of the 28 provinces, which were all in the southern region: Shanghai, Zhejiang, Fujian, Jiangxi, Hunan, Guangdong, and Hainan. Conversely, the coefficients for Sichuan (0.672), Chongqing (0.646), and Guizhou (0.887) were significantly larger, suggesting that R&D investment in these three provinces can substantially reduce the emissions of residents. In Qinghai, Gansu, Shaanxi, Hebei, Tianjin, Beijing, Shandong, and Henan, the CCD increased by 0.169–0.344 for each percentage point increase in the proportion of R&D investment.

Table 3-7. Coefficients of factors affecting the degree of CCD.

Province	R&D Investment	Regulation	Energy Structure	GDP per Capital	Per Capital Cropland
Beijing	0.270	0.000	0.088	-0.622	-0.231
Tianjin	0.306	-0.001	0.113	-0.711	-0.251
Hebei	0.286	0.012	0.142	-0.699	-0.171
Shanxi	0.234	0.028	0.147	-0.621	-0.101
Shandong	0.344	-0.017	0.178	-0.867	-0.226
Henan	0.296	0.001	0.209	-0.838	-0.117
Inner Mongolia	0.122	0.013	0.083	-0.385	-0.073
Liaoning	0.080	-0.053	0.015	-0.642	-0.386
Jilin	0.078	-0.127	-0.097	-0.703	-0.249
Heilongjiang	0.169	-0.130	-0.138	-0.650	-0.099
Shanghai	-0.387	-0.117	0.299	-0.932	-0.431
Jiangsu	0.004	-0.146	0.262	-0.954	-0.325
Zhejiang	-0.442	-0.143	0.304	-0.869	-0.260
Anhui	0.063	-0.151	0.255	-0.926	-0.245
Fujian	-0.931	-0.228	0.398	-0.828	-0.166
Jiangxi	-0.316	-0.250	0.323	-0.812	-0.292
Hubei	0.035	-0.169	0.258	-0.803	-0.146
Hunan	-0.002	-0.199	0.327	-0.780	-0.317
Guangdong	-0.176	-0.063	0.480	-0.925	-0.770
Guangxi	0.297	-0.038	0.422	-0.214	0.576
Hainan	-0.133	-0.072	0.419	-0.182	0.161
Chongqing	0.646	-0.112	0.057	-0.282	0.446
Sichuan	0.672	-0.004	-0.095	0.049	0.348
Guizhou	0.887	-0.143	0.163	-0.095	0.831
Yunnan	0.000	0.000	0.000	0.000	0.000
Shaanxi	0.224	0.043	0.131	-0.623	0.099
Gansu	0.213	0.029	-0.005	-0.098	0.186
Qinghai	0.326	0.041	0.025	0.073	0.206
Ningxia	0.100	0.026	0.030	-0.204	0.126
Xinjiang	0.000	0.000	0.000	0.000	0.000

Province	Hydropower	Temperature	Average Education year	Urbanization
Beijing	-0.015	-0.553	-0.223	0.087
Tianjin	-0.012	-0.604	-0.178	0.080
Hebei	0.035	-0.397	-0.062	0.042
Shanxi	0.022	-0.219	0.020	-0.014
Shandong	0.022	-0.559	-0.027	0.059
Henan	0.053	-0.287	0.134	-0.006
Inner Mongolia	-0.053	-0.137	-0.108	-0.004
Liaoning	0.704	-0.522	0.229	-0.345
Jilin	2.091	0.015	0.481	-0.627
Heilongjiang	2.431	0.410	0.420	-0.744
Shanghai	-0.028	-0.734	0.137	0.319
Jiangsu	0.010	-0.666	0.103	0.171
Zhejiang	0.005	-0.708	0.122	0.361
Anhui	0.032	-0.589	0.096	0.145
Fujian	0.071	-1.213	0.107	0.844
Jiangxi	0.065	-0.872	0.040	0.332
Hubei	0.067	-0.520	0.058	0.096
Hunan	0.061	-0.878	0.036	0.070
Guangdong	0.045	-1.969	0.224	0.241
Guangxi	-0.087	-1.513	0.269	-0.046
Hainan	0.035	-2.190	0.467	0.132
Chongqing	-0.020	-0.024	-0.282	-0.078
Sichuan	0.027	0.130	-0.315	-0.148
Guizhou	-0.085	-0.399	-0.357	-0.104
Yunnan	0.000	0.083	0.000	0.000
Shaanxi	0.009	0.069	0.153	-0.069
Gansu	0.019	0.214	0.014	-0.287
Qinghai	-0.002	0.177	-0.036	-0.372
Ningxia	-0.006	0.221	0.062	-0.280
Xinjiang	0.000	0.000	0.000	0.000

Previous studies [71] have shown that the management of industrial pollution contributes to rural energy transitions and increases the environmental awareness of the population. Accordingly, we included the ratio of investment in industrial pollution control to the industrial added value as a factor in the model. Figure 3-10b shows the coefficients indicating the impact of the government's investment in industrial pollution control as a proportion of industrial added value on the degree of coordinated coupling. The promotion and weakening effects were distinctly and spatially clustered. Shaanxi, Gansu, Qinghai, Ningxia, Shanxi, Hebei, and Inner Mongolia, all in the northern region, showed enhanced effects, indicating that the government's efforts in industrial pollution control in these provinces have contributed to the reduction in emissions. Twenty-one provinces and cities exhibited a weakening effect, particularly along the southeastern coast.

Higher education correlated with greater environmental awareness but did not guarantee eco-friendly behaviors because of factors such as personal values, cultural contexts, and economic incentives [100]. In this study, we calculated the effect of the average years of education on coordinated coupling. As shown in Figure 3-10c, the average number of years of education has both promoting and weakening effects on coordinated coupling. In Beijing, Tianjin, Hebei, Inner Mongolia, Shandong, Chongqing, Sichuan, Guizhou, and Qinghai, the average number of years of education weakened coordinated coupling, suggesting that in these regions, the average number of years of education had a negative effect on emissions from the residential sector rather than reducing both in the same direction. In six provinces and municipalities, the average years of education increased the CCD by 0.267 to 0.481 in Heilongjiang and Jilin and by 0.122 to 0.267 per year in Henan, Shaanxi, Yunnan, and Guangxi.

Electricity consumption, as a portion of total energy consumption, is a measure of the energy mix; an increase in the share of electricity consumption means that electricity has replaced traditional solid fuels (e.g., firewood and coal) for heating and cooking, resulting in reduced AP emissions from households [101]. As shown in Figure 3-10d, the energy mix in all provinces and cities, except for Sichuan, Gansu, Jilin, and Heilongjiang, contributed to the development of harmonization and coupling, which indicates that an increase in the share

of electricity consumption in most provinces and cities led to a reduction in emissions. In the southeast, including Guangxi, Guangdong, Fujian, and Hainan, the CCD increased from 0.327 to 0.480 for every percentage point increase in the share of the electricity consumption structure. Similarly, in Guizhou, Hunan, Hubei, Anhui, Zhejiang, Jiangsu, and Jiangxi, the CCD increases from 0.209 to 0.327 for each percentage point increase in the share of the electricity consumption structure.

Hydropower directly reduces the use of fossil fuels, thereby reducing the residential AP and CO₂ emissions. However, hydropower has regional variability. Provinces and cities rich in hydropower resources have a greater potential to reduce carbon emissions and air pollution, whereas regions dependent on fossil fuels for power generation have less potential [102]. As shown in Figure 3-10g, each percentage increase in the proportion of hydroelectric power generation led to an increase in the CCD, ranging from 2.431 to 0.071 in Heilongjiang, Jilin, Liaoning, and most provinces and cities in the southeast, with Jiangsu and Zhejiang being significant contributors, enhancing the degree of coupling. This suggests that increasing the proportion of hydropower generation in the southeastern and northeastern provinces could lead to reductions in emissions from the resident population. Weaker effects were observed in Beijing, Tianjin, Inner Mongolia, Shanghai, Guangxi, Chongqing, Guizhou, Qinghai, and Ningxia.

The relationship between per-capita GDP and air pollution differs across regions. In the study by Xu [103], GDP per capita was considered to have a negative effect, except in the Beijing–Tianjin–Hebei region, Yangtze River Delta, and South China, where it is believed to have a positive effect. Aslam [104] found that GDP per capita negatively affects CO₂ emissions, whereas the square of the GDP per capita positively impacts CO₂ emissions. In this study, except for the Sichuan and Qinghai regions, GDP per capita was found to exert a weakening effect on coordinated coupling (Figure 3-10e). This result suggests that in most regions, GDP per capita does not simultaneously promote the reduction of residential air pollution and CO₂. Furthermore, the distribution of this influence in terms of strength was spatially clustered. In the southeastern regions, including Shandong, Henan, Hubei, Hunan, Jiangsu, Anhui, Zhejiang, Fujian, Jiangxi, and Guangdong, the CCD decreased by 0.954–

0.780 for each unit increase in GDP per capita. In Heilongjiang, Jilin, Liaoning, Hebei, Tianjin, Beijing, and Shanxi, the CCD decreased from 0.780 to 0.621 for each unit increase in GDP per capita.

Cropland areas represent a potential reservoir of biomass fuel resources, which significantly influence residential fuel choices. Consequently, we assessed the cropland area as a possible influencing factor [105]. As shown in Figure 3-10f, in the western region (Guangxi, Guizhou, Chongqing, Shanxi, Ningxia, Gansu, Qinghai, and Sichuan), an increase in the per capita arable land area resulted in an increase in the degree of coupling coordination. This led to a decrease in the degree of coupling in the southeastern region and in North China. The east–west distribution of this difference was significant.

Temperature affects residential emissions through several pathways that influence energy demand, air pollution dispersion, residential activity patterns, and chemical reactions involving pollutants. As depicted in Figure 3-10h, temperature had a weakening effect on the synergistic emission reduction in the southeastern region and a promoting effect on the CCD in the western region, particularly in Sichuan, Qinghai, Gansu, Ningxia, and Heilongjiang.

An increase in urban population typically leads to increased energy consumption and emissions. Although urbanization can, to some extent, mitigate the growth of emissions by enhancing energy use efficiency and upgrading the industrial structure, cities with high population densities tend to have more severe AP and CO₂ emission issues [98,106]. As shown in Figure 3-10i, there was a significant difference between the eastern and western regions in terms of the impact of population distribution on the CCD. However, in contrast to the effect of temperature, the impact of per capita cropland on the degree of coupling coordination varied. The southeastern and northern parts of China were associated with a promotional effect, whereas the western part played a weakening role.

In summary, in the southeastern region, R&D investment, government investment in industrial pollution control, the proportion of electricity consumption, GDP per capita, cropland per capita, and temperature weakened the degree of CCD in the residential sector, whereas hydroelectricity generation and the proportion of the urban population enhanced the

degree of coupling coordination. In the western region, R&D investment, government investment in industrial pollution control, the proportion of electricity consumption, cultivated land area per capita, temperature, and the proportion of the urban population contributed to the CCD. The average years of education in six provinces and cities, Heilongjiang, Jilin, Henan, Shaanxi, Yunnan, and Guangxi, had a boosting effect on the CCD.

3.6 Discussion and Policy Implications

3.6.1. Regional Emission Characteristics of the Residential Sector Deviated from the Previous North–South Divide

Previous studies have primarily focused on emission disparities between the northern and southern regions during the winter heating seasons, as well as emissions from rural residents in the north. For instance, Ma et al. [107] explored clean and low-carbon heating pathways in northern China by 2035. Zhang et al. [17] analyzed reducing multiple air pollutants in northern China via resource sharing. Wang et al. [108] assessed winter heating’s impact on air quality in northern China. In contrast, this study encompassed both rural and urban residential emissions in the northern and southern regions. In the northern region, centralized heating managed by the government or heat plants results in emission characteristics and drivers that are distinct from those that depend on the fuel choices made independently by residents and usage times. Hence, these aspects were not addressed in this study.

Following the implementation of APPCAP 2013 and BSAP 2018, residential air pollution emissions have seen a more significant reduction in the north than in the south, with the disparity widening after policy implementation. As discussed in Figure 3-8, the article suggests that energy upgrading and substitution policies for residential emissions are best prioritized in the more populated southern regions. This approach is likely to be more effective in reducing pollutant emissions. Furthermore, the LMDI decomposition analysis of

residential pollution emissions classified the 30 provinces into four distinct categories. The first comprised regions with high demographic influence, including Beijing, Tianjin, Hebei, Shanxi, Henan, Shandong, Shaanxi, Zhejiang, Jiangxi, Guangdong, and Yunnan. The second category included provinces with high CO₂ impacts per unit of AP, such as Liaoning, Gansu, Ningxia, Qinghai, Xinjiang, Shanghai, Hubei, and Hunan. The third category included provinces with higher emission factors, namely Hainan, Guizhou, Sichuan, Chongqing, Guangxi, Jiangsu, Fujian, Anhui, and Yunnan. The fourth type, referred to as the mixed type, includes Jilin, Inner Mongolia, and Heilongjiang.

3.6.2. Need for Synergistic Emission Reductions in the Residential Sector

As detailed in Sections 3.5.1 and 3.5.3, there is a large difference between the AP per unit of CO₂ brought by the residential sector and the CO₂ emissions per unit of AP, and the coordination between CO₂ and PM remains low. Primarily, this is because CO₂, a long-life-cycle pollutant [109], does not have an immediate policy impact on emissions reduction. In contrast, immediate results were observed in terms of the reduction in short-life-cycle AP pollutants once air pollution abatement policies were implemented. These differences were evident in air quality improvement, stronger social consensus, higher participation, and easier policy promotion. However, in a recent study [110], the social cost of CO₂ in 2017 was comparable to the health impact of PM_{2.5}. In another study [111], it was shown that PM_{2.5} pollution in China resulted in a health-related economic burden of 1516 billion yuan in 2020, while CO₂ emissions cost society 1081.1 billion yuan. The main regions bearing these social costs in terms of both PM_{2.5}-related health impacts and CO₂ emissions were the BTH and YRD urban conglomerations and certain central metropolitan areas. The convergence of social costs highlights the importance of addressing both CO₂ and PM_{2.5} together. Policymakers should consider integrated strategies targeting long-term climate change mitigation and immediate air quality improvement. This approach could yield synergistic benefits, maximizing the positive impact on public health and the environment while optimizing pollution control resource allocation.

3.6.3. Emission Reduction Paths of Residential Sectors in Key Regions

To better understand the driving relationship between social factors and emissions, this paper attempts to combine the results of the LMDI model and the GTWR model to analyze the focus areas of emission reduction policies. For specific data references, please refer to Tables 3-4 and 3-7.

In the BHT regions (Beijing, Tianjin, Hebei, Shanxi, Shandong, and Henan), the population size was the leading factor in residential emissions, averaging 613 (Table 3-4), with Shandong Province reaching a high population of 1124. In Shandong Province, the relative contributions of factors driving (Table 3-7) cointegration were R&D investment (0.344), electricity consumption (0.178), urbanization (0.059), and hydroelectricity (0.022), with R&D and electricity consumption being particularly influential. Notably, the energy emission factors in Beijing and Tianjin were 404.72 and 205.57, respectively, in contrast to other regions where the emission factors contributed to pollution reduction. This indicates that energy policies, such as switching from coal to electricity and natural gas in Hebei, Shanxi, Shandong, and Henan, significantly impacted residential emissions. In Beijing–Tianjin–Hebei and the neighboring regions, synergies rose by 0.289 for each percentage point increase in R&D investment and by 0.146 for each percentage point increase in electricity consumption.

In the YRD regions, which include Shanghai, Jiangsu, Zhejiang, and Anhui, the contributions of the energy emission factor were significantly high in Jiangsu and Anhui, at 8884.9 and 4995.3 (Table 3-4), respectively, indicating substandard energy quality in the residential sector, low combustion efficiency, and the need for stove upgrades in these provinces. In Jiangsu, the contribution of the population factor to the emission factor was 1118. In Jiangsu, the average years of education, R&D investment, electricity consumption ratio, urbanization, and hydropower generation were found to enhance the coordination of particulate matter and CO₂ emissions, with the electricity consumption ratio and urbanization having the largest absolute values (Table 3-7) of 0.262 and 0.171, respectively. The

government can reduce residential sector emission factors and population size by implementing measures to address the high contributions of residential sector emission factors and population size. For example, increasing the share of electricity consumption can lead to a decrease in coal usage, thereby reducing the sector's emission factors, while enhancing urbanization can boost energy use efficiency, thereby reducing air pollutant emissions and population contributions to the AP. We observed the same pattern in Anhui Province, where the average years of education, R&D investment, share of electricity consumption, urbanization, and hydropower generation were found to enhance the coordination of PM and CO₂, with the largest contributions from electricity consumption and urbanization. In Zhejiang Province, the population's size made the highest contribution to the emission factors, and four factors, such as the average years of education, electricity consumption ratio, urbanization, and hydropower generation, contributed to the coordination of particulate matter and CO₂. However, urbanization had the strongest effect (0.361), followed by the electricity consumption ratio (0.304), both of which were higher than those in Jiangsu Province. In Shanghai, urbanization (0.319), the share of electricity consumption (0.299), and years of education per capita (0.137) were conducive to improving the coordination of particulate matter and CO₂. Coordination coupling is currently the primary factor influencing residential emissions in Shanghai (14,145)

3.6.4. Limitations and Future Research

Emission factors for the residential sector in the MEIC database were derived from Tsinghua University-led household survey data for the residential sector [112]. Given the limitations of official energy statistics reports, household surveys have emerged as a direct method for gathering data. However, these surveys yield varying results for the rural residential sector, owing to the differences in the survey samples, years, and methods of analyzing and estimating energy consumption [105] [112,113]. In this study, we used provincial panel data for the assessment and did not consider specifics at the municipal level. For example, the heavily polluted Fen Wei Plain is divided at the municipal level; therefore,

we could not assess the drivers in this region. Resolving this limitation will be a worthwhile goal in future research.

The GWTR model analyzes the drivers affecting the degree of CCD but does not delve deeper into their underlying causes. For example, this study confirms that R&D investment plays a role in weakening synergistic coupling in Shanghai, Zhejiang, Fujian, Jiangxi, Hunan, Guangdong, and Hainan provinces. Previous studies [114,115] suggest that higher R&D investment in the industrial sector may lead to higher productivity and an energy rebound effect and may lead to higher carbon and pollution emissions. In addition, some studies have shown that technological improvements can enhance the energy efficiency of residential areas [116]. Studies such as this can help us understand the mechanisms of the social factors behind emission reductions and provide a direction for future research.

Finally, although the model constructed in this paper is designed to analyze emissions from the residential sector, given that both the residential and transportation sectors are significantly influenced by individual behavior, income levels, and policy impacts, it is worth exploring whether the model can be applied to the transportation sector as well. This could be a topic for future research.

3.7. Conclusions

The objective of this study was to quantify the impact of social factors on the synergistic emission reduction of China's residential sector and to optimize the emission reduction route. This study used a nested structure of CCD and GTWR to extend and validate the decomposition factors of LMDI, and the conclusions are as follows:

1. The emissions from the residential sector predominantly stem from coal consumption, with coal use accounting for more than 50% of residential emissions in 12 of the 30 provinces.
2. The LMDI decomposition results showed that energy emission factors and population size are the main drivers of pollutant emissions, suggesting they should be key targets for future reduction efforts. Additionally, the traditional north–south division no longer

accurately categorizes residential emissions post-2015. A new classification was proposed: high demographic influence (Beijing, Tianjin, Hebei, Shanxi, Henan, Shandong, Shaanxi, Zhejiang, Jiangxi, Guangdong, and Yunnan); high CO₂ impacts per unit of AP (Liaoning, Gansu, Ningxia, Qinghai, Xinjiang, Shanghai, Hubei, and Hunan); higher emission factors (Hainan, Guizhou, Sichuan, Chongqing, Guangxi, Jiangsu, Fujian, Anhui, and Yunnan); and mixed type (Jilin, Inner Mongolia, and Heilongjiang).

This new classification provides a more nuanced understanding of regional emission patterns and can inform targeted policy interventions. For instance, regions with high demographic influence may benefit from population control measures and urban planning strategies to mitigate emissions. Areas with a high CO₂ impact per unit of AP could focus on improving energy efficiency and transitioning to cleaner energy sources. Regions with higher emission factors should prioritize technological upgrades and stricter emission standards for residential appliances and heating systems.

3. To explore synergistic emission reduction in the residential sector, we utilized a nested CCD and GTWR model. The results indicate that northern regions have higher average coupling degrees than southern ones. The findings show that in the southeastern region, hydroelectricity generation and the proportion of the urban population enhanced the degree of coupling coordination. In the western region, R&D investment, government investment in industrial pollution control, the proportion of electricity consumption, cultivated land area per capita, temperature, and the proportion of the urban population contributed to the CCD.

The spatial heterogeneity of these factors underscores the need for tailored regional policies to address residential carbon emissions effectively. In the northeastern region, factors such as industrial structure and energy consumption patterns played a more significant role in influencing the coupling coordination degree. Future research should focus on developing more granular, city-level analyses to further refine our understanding of the complex interactions between socioeconomic factors and residential emissions across diverse urban landscapes.

4. After 2015, emissions driven by population factors in southern cities surpassed those in northern regions. This shift can be attributed to the rapid urbanization and economic

development occurring in southern China during this period. As more people migrated to southern cities for employment opportunities, the demand for energy and resources increased significantly. Consequently, the residential emissions of these growing urban centers expanded, outpacing the emissions growth in the more established northern cities.

Abbreviation

Variable s	Description	Unite
AP	The concentration of air pollutants.	metric ton
U_{CO_2}	CO ₂ emissions.	metric ton
E_{AP}	All pollutants' emissions.	metric ton
E_{coal}	Coal consumption.	standard coal equivalent
E_{total}	Energy consumption of the residential sector	standard coal equivalent
P	Air pollution per unit of coal.	—
Z, Pop	Population.	people
H	The concentration of pollutants per CO ₂ emission unit.	—
R	The CO ₂ emissions for each unit of pollutant released.	—
St	The proportion of coal used in the overall energy usage of the residential sector	—
So	The amount of energy used per GDP unit in the residential sector.	—
E	GDP per capita.	CNY
LMDI	Logarithmic mean Divisia index decomposition	—
CCD	Coupling coordination degree	—
MP	Particulate matter	—

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Supplementary Materials

S3-1 Paper list (digital data)

S3-2. MEIC calculation formula

Considering that the MEIC database (<http://www.meicmodel.org>, Multi-resolution Emission Inventory for China) is based on the iterative updating technique for emission estimation, we chose this database. The MEIC database is modeled as follows:

$$E_{psk} = A_{ps} \times \sum_t (X_{pst} \times EF_{pskt} \times \sum_a (C_{psta} \times (1 - \mu_{ka})))$$

p signifies the province, s indicates the emission source, k denotes air pollutants or CO₂, t represents manufacturing technologies, and a stand for air pollution control technologies. Additionally, A symbolizes the activity rate, X denotes the proportion of a particular manufacturing technology, EF represents the uncontrolled emission, and μ signifies the removal efficiency. For a comprehensive understanding of the emission factors and technical details, readers are directed to two subsequent articles (Li,M.,2017; Zheng,B.,2018).

Li, M., Liu, H., Geng, G., Hong, C., Liu, F., Song, Y., ... & He, K. (2017). Anthropogenic emission inventories in China: a review. *National Science Review*, 4(6), 834-866.

Zheng, B., Tong, D., Li, M., Liu, F., Hong, C., Geng, G., ... & Zhang, Q. (2018). Trends in China's anthropogenic emissions since 2010 as the consequence of clean air actions. *Atmospheric Chemistry and Physics*, 18(19), 14095-14111.

Table S3-3. Disorder Class

Disorder Class	Type (Disorder)	Level (Disorder)
[0,0.1]	Extremely dysfunctional recession	1
[0.1,0.2]	Severe dysfunctional recession	2
[0.2,0.3]	Moderate dysregulation recession	3
[0.3,0.4]	Mild dysregulation recession	4
[0.4,0.5]	On the verge of a dysfunctional recession	5
[0.5,0.6]	Barely coupled coordination	6
[0.6,0.7]	Primary coupling coordination	7
[0.7,0.8]	Intermediate coupling coordination	8
[0.8,0.9]	Good coupling coordination	9
[0.9,1]	Quality coupling coordination	10

Note: Quoting from Chen's paper (Chen, 2023).

Chen, S., Tan, Z., Mu, S., Wang, J., Chen, Y., He, X. J. S. C., & Society. (2023). Synergy level of pollution and carbon reduction in the Yangtze River Economic Belt: Spatial-temporal evolution characteristics and driving factors. 98, 104859.

Chapter 4

UNDERSTANDING EMISSION TRENDS, RE-GIONAL DISTRIBUTION DIFFERENCES, AND SYNERGISTIC EMISSION EFFECTS IN THE TRANSPORTATION SECTOR IN TERMS OF SO-CIAL FACTORS AND ENERGY CONSUMPTION

Chapter 4

UNDERSTANDING EMISSION TRENDS, REGIONAL DISTRIBUTION DIFFERENCES, AND SYNERGISTIC EMISSION EFFECTS IN THE TRANSPORTATION SECTOR IN TERMS OF SOCIAL FACTORS AND ENERGY CONSUMPTION

4.1 Introduction

The Sustainable Development Goals of Good Health and Well-being (SDG 3) and Climate Action (SDG 13) are relevant to sustainable development. The Intergovernmental Panel on Climate Change (IPCC) proposed a comprehensive framework for climate change, wherein socio-economic development has caused the accumulation of greenhouse gas and aerosol emissions, contributed to atmospheric pollution, reinforced the greenhouse effect, and altered the future climate. The transportation sector ranks third among China's major sources of greenhouse gas emissions, following closely behind the power generation industry [1–3]. Therefore, to support and guarantee the attainment of the country's 2030 emission reduction goal, the transportation industry will need to undertake the arduous task of emission reduction in the coming decades. At the same time, the use of large amounts of fuel by the transportation sector has brought about an increase in air pollutants such as PM, CO, NO_x, VOC, and SO₂.

Air pollution and CO₂ emissions share similar root sources [4,5], which has prompted concerns about how to reduce CO₂ emissions while controlling air pollution. This has become a hot topic of discussion. The China Center for Environmental Politics and Economic Policy Research (CCEEPR) provides a definition of the twofold beneficial effects of air pollution

reduction and carbon emission reduction [6]. Firstly, in the process of controlling greenhouse gas emissions, other local pollutant emissions (e.g., SO₂, NO_x, CO, VOC, and PM) can be decreased. Secondly, in the process of controlling local pollutant emissions and carrying out ecological construction, CO₂ and other pollutant emissions can be reduced or absorbed. Consequently, the feasibility of reducing CO₂ emissions while alleviating air pollution and fostering sustainable development, the presence of synergistic emission effects in policy implementation and the factors influencing these effects, and strategies to enhance policy efficiency have attracted considerable academic interest. Given the significant health risks linked to PM_{2.5} and NO₂ emissions from the transportation sector [7], the particularly urgent issue of PM_{2.5} and O₃ emissions in China's air pollution landscape [8], the role of NO_x as a major precursor to atmospheric ozone and PM_{2.5} [9,10], and the impact of VOCs (volatile organic compounds) on particulate matter abatement, we therefore extended the study to include CO₂, PM_{2.5}, PM₁₀, CO, SO₂, NO_x, and VOC in order to analyze the issue from an all-encompassing societal perspective.

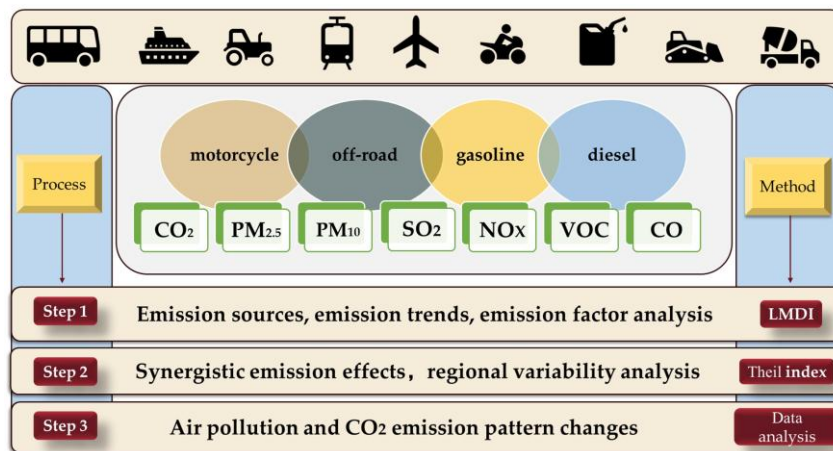


Figure 4-1. Analysis structure. *Note: this study analyzed 10 types of emissions from four pollution sources. On the left side is the sequence of research steps, while the corresponding research methods are presented on the right side (source: created by the authors).*

This article is structured as follows: In Section 4.2 presents a review of the previous research. Section 4.3 details our research method and data sources. In Section 4.4 summarizes the results (Figure 4-1); Sections 4.1 and 4.2 include an analysis of the pollution sources, emission trends, and LMDI decomposition results; Sections 4.3 and 4.4 delve into the synergistic effect analysis and regional disparities. In Section 4.5, we discuss the homogeneity and heterogeneity factors, as well as propose some policy recommendations. Finally, Section 4.5 concludes by summarizing our findings.

4.2 Objectives of this study

The subject of this study is emissions from the transportation sector. Emissions from the transportation sector are generally categorized into two main types: on-road and off-road mobile sources. Off-road transportation includes activities such as fishing, international aviation, domestic aviation, rail, international navigation, domestic navigation, pipeline transport, and other non-specified transport modes. On-road mobile sources primarily comprise agriculture and forestry vehicles, cars, light-duty trucks, buses, heavy-duty trucks, other fleet vehicles, and motorcycles.

This study utilizes the MEIC (Multi-resolution Emission Inventory for China) database, in which the statistical classification of air pollutant emissions is divided into on-road mobile sources and off-road transportation. The on-road mobile sources are further categorized into diesel vehicles, gasoline vehicles, and motorcycles. For detailed classifications, please refer to Table S4-3 in the supplementary materials.

4.3 Literature Review

4.3.1. Studies on Emission Trends and Synergistic Emission Effects

Dong's [11] study filled a gap in the understanding of the synergistic effects of air pollution and carbon emission reductions across all provinces in China. It assessed provincial CO₂ emission reductions from an economic policy perspective and predicted synergistic

reduction benefits. Li [12] used data from 18 manufacturing sectors and demonstrated, from the demand theory perspective, that CO₂ and SO₂ have a substitution effect. However, this study did not fully consider the potential impacts of future technological advancements and policy changes. Subsequent scholars began to assess the impact of one aspect, either CO₂ or air pollution, on the other. Yang [13] investigated the air quality benefits of China's goal to peak carbon emissions by 2030, noting reductions in SO₂, PM_{2.5}, and NO_x emissions across agriculture, electricity, industry, transportation, and construction sectors. Lu [14] assessed the National Air Pollution Prevention and Control Action Plan's impact on major pollutants in the Jing-Jin-Ji region, finding that PM_{2.5} reduction had the most significant synergistic effect on CO₂ reduction in Beijing–Tianjin–Hebei. However, both studies may have overestimated policy impacts. According to Chen [15], the synergistic effect of carbon emissions reduction surpasses that of pollution reduction and disaggregates the air pollutants. They found that the synergistic emission reduction effect of SO₂ was greater than that of PM_{2.5}.

Recent discussions on synergistic mechanisms and social cost estimates have increased. Wang [16] examined the collaborative governance of climate change and air pollution, finding that reducing carbon emissions by 1000 tons in China's industrial sector also reduced air pollutants by 1 ton. However, the study neglected the adaptability of governance mechanisms under varying policies. Yuan [17] examined China's energy transition's combined impact on air quality and carbon emissions. Using a 2025 scenario analysis, the study simulated pollutant concentration changes, emphasizing end-of-pipe control measures for pollutants while overlooking socio-economic costs. Shu [18] examined the influence of the "Three-Year Action Plan" in China's "2+26" cities (Beijing, Tianjin, and 26 other prefecture-level cities in the Jing-Jin-Ji area) on reducing air pollution and mitigating climate change. The study found that nearly half of these counties increased their CO₂ emissions while reducing their air pollutant emissions. However, it may have overestimated policy impacts and overlooked economic, social, and technological changes. Shu's [19] study investigated feasible pathways to achieve PM_{2.5} air quality standards and their synergistic benefits for CO₂ emission reductions by 2030 in northern Chinese cities. Zha [20] developed

a system to evaluate the efficiency of urban pollution and carbon emission reduction governance. The results showed a 38.07% increase in synergistic governance efficiency among Chinese cities from 2006 to 2020. However, the study did not examine the impact of specific industries on pollution and carbon emissions. Xian [3] identified synergistic effects between pollution and carbon reduction policies in China's electricity, industry, transportation, residential, and agricultural sectors. The study showed that current emission reduction policies significantly reduced major air pollutant emissions and slowed CO₂ emission growth. These synergistic effects varied across sectors, but regional heterogeneity was not deeply explored. Xu [21] demonstrated a clear and strengthening synergistic effect between CO₂ and air pollutant emissions in China's industrial sector. Synergies between coal-related carbon emissions and air pollutants are increasing, whereas those between gas-related emissions and pollutants are declining. However, the study overlooked regional differences in industrial structure, energy consumption, and pollution control affecting these synergies.

4.3.2. Status of Research on Synergistic Effects in the Transportation Sector

Alimujiang [22] (2020) highlighted the advantages of electric private cars, taxis, and buses in reducing carbon dioxide and air pollutant emissions in Shanghai. However, the study did not thoroughly evaluate the economic costs of widespread electric vehicle adoption, including infrastructure construction and maintenance expenses. Jiao [2] quantitatively analyzed the synergistic effects of CO₂ and air pollutants in Guangzhou's transportation sector, evaluating emissions across various urban transportation subsectors. However, the study inadequately addressed regional differences in transportation structure, energy consumption, and pollution control measures. Duan [23] assessed the traditional strategies of Chongqing's road traffic industry, finding that changing transportation trends effectively reduced air pollutants and CO₂ emissions in the short term. The study highlighted the critical role of clean electricity production for electric vehicle development in the medium-to-long

term. Guo [24] analyzed and forecasted energy consumption and emissions in the Beijing–Tianjin–Hebei region, concluding that optimizing the energy structure most effectively reduces emissions in the road traffic and aviation sectors. Dong [25] used the LEAP framework and advanced scenarios to estimate the impact of CO₂ emission reductions on air pollution in Zhengzhou’s road traffic. In Fu’s study [26], a framework for scenario analysis was constructed, showing that reducing air pollution and greenhouse gases through the development of compact cities can be achieved by 2050 with the widespread use of new energy vehicles and decarbonization of energy sources. These studies are all based on model-driven scenario analyses, which are beneficial in providing policymakers with potential outcomes under different policy choices, thereby facilitating more informed decision-making. However, this approach is overly reliant on model calculations and policy assumptions, neglecting inconsistencies with actual policy developments, thereby affecting the applicability of the analysis results. Therefore, we believe that modeling analysis based on historical data is essential.

4.3.3. Research Status Summary

The aforementioned studies generally show that efforts to reduce carbon emissions often also help reduce air pollution, and vice versa. However, the effects can vary depending on the region, industry, and type of pollutant or emission being studied. Almost all studies on synergistic emission reduction in the transportation sector rely heavily on calculations and assumptions, potentially overlooking real-world policy developments. This may affect the applicability of their results. Two studies have specifically focused on synergistic emissions reductions in the transportation sector and have not employed scenario analyses. A study [27] focused on the impact of carbon markets and environmental regulations on synergistic emission reductions in the transportation sector, with the disadvantage that it did not analyze the impact of factors such as energy mix. Another study [28] developed a co-benefit impact model for reducing carbon emissions and air pollutants. According to that study, the primary driving factors behind this synergistic effect are energy efficiency and industrial structure.

Furthermore, transportation synergies are typically greater in areas with stricter environmental regulations. However, there are still some shortcomings. For example, while the most serious air pollution in China is PM and O₃ pollution [29], the dependent variable used in the model was only the emission reduction of SO₂, and other pollutants were not considered. They utilized the IPCC model to determine CO₂ emissions, which, as a “top-down” model, incorporates a multitude of uncertainties related to carbon emissions, as identified by Loo [30].

Therefore, our study utilized a “bottom-up” model database to calculate the synergistic effect between carbon dioxide and air pollutants in transportation. This study also incorporated the following seven factors that affect emissions into one model and quantified each factor: air pollution emissions that lead to carbon dioxide emissions, carbon dioxide emissions accompanied by air pollutant emissions, pollution emission intensity in the transportation sector, energy mix in the transportation sector, energy consumption intensity in the transportation sector, economic growth, and population (Table 4-2). The innovation of this study is the inclusion of the transportation sector’s pollution emission intensity, an indicator that allows for the status of vehicle and fuel upgrades in 30 provinces to be directly compared. The synergistic effects between CO₂ and air pollution are also quantified, which facilitates the analysis of regional differences. The above advances provide a reliable basis for policy implementation.

4.4 Materials and Methods

4.4.1. MEIC Calculation

Internationally, there are two ways to measure emissions: one is a top-down model that calculates only according to energy consumption, and the other is a bottom-up model that calculates according to the specifics of each sector, such as the number of vehicles in the transportation sector, the number of passengers, and other degrees of activity. Generally, the bottom-up calculation method is more accurate [12]. We chose the MEIC database (Multi-

resolution Emission Inventory for China, <http://www.meicmodel.org>) as it relies on iterative updates to technology for the estimation of emissions.

The MEIC database is modeled as follows:

$$E_{psk} = A_{ps} \times \sum_t (X_{pst} \times EF_{pskt} \times \sum_a (C_{psta} \times (1 - \mu_{ka}))) \quad (4-1)$$

where p denotes the province, s denotes the emission source, k denotes the air pollutants or CO₂, t denotes the manufacturing technologies, and a denotes the air pollution control technologies. A represents the activity rate, X represents the proportion of a specific manufacturing technology, EF represents the unmitigated emissions, and μ represents the removal efficiency. The determination of the emission factors and the technical explanations have been detailed in two previously published articles [12,31].

4.4.2. Model Construction

Firstly, the Kaya equation [32] is widely used internationally to estimate CO₂ emissions. Its expression is as follows:

$$CO_2 = \frac{CO_2}{Energy} \times \frac{Energy}{GDP} \times \frac{GDP}{Pop} \times Pop \quad (4-2)$$

As shown in Equation (4-1), CO₂ emissions are composed of four factors, listed from left to right in sequence: CO₂ per unit of energy consumption, energy consumption per unit of GDP, GDP per capita, and population (Pop, Table 4-1). Through this equation, carbon emissions are linked to social development factors. This study further extends the application of the Kaya equation to air pollutant emissions.

Table 4- 1. The definitions of the driving factors (for Equations (4-2)– (4-4)).

Variables	Description	Unite
AP	The concentration of air pollutants.	metric ton
U_{CO_2}	CO ₂ emissions.	metric ton
E_{AP}	All pollutants' emissions.	metric ton
E_{gaso}	Gasoline consumption.	standard coal equivalent
E_{total}	Energy consumption of the transportation sector.	standard coal equivalent
G	GDP.	CNY
D, Pop	Population.	people
H	The concentration of pollutants per CO ₂ emission unit.	—
C	The CO ₂ emissions for each unit of pollutant released.	—
St	The proportion of gasoline used in the overall energy usage of the transportation sector.	—
So	The amount of energy used per GDP unit in transportation.	—
E	Per capita GDP.	CNY

4.4.3. Decomposition Analysis

The fundamental concept of exponential decomposition involves initially establishing a control function that connects the aggregate to be decomposed with specific predefined factors of interest. With the control function in place, a variety of decomposition techniques can be employed to measure the effects of these factors' changes on the aggregate. This approach allows for a clear and systematic analysis of how different elements contribute to the overall aggregate, providing insights into their individual impacts [31]. Therefore, decomposition analysis can help to increase our understanding of the magnitude of the role of different driving factors. Broadly speaking, there are several ways to perform this: index decomposition analysis (IDA), structural decomposition analysis (SDA), arithmetic mean division index decomposition (AMDI), and logarithmic mean division index decomposition (LMDI).

While AMDI has a residual term [33], SDA is more data-demanding and requires input–output tables [34]. However, LMDI only requires time series data. LMDI was proposed by

Ang in 1998 and derived from the IDA method, and it has been widely used in energy-related analysis. It has the advantage of having no residual terms and is easy to interpret [35], and it has been applied to the synergistic abatement of air pollution and carbon dioxide in pioneering research [28,36–38].

$$AP = \frac{AP}{U_{CO_2}} \times \frac{U_{CO_2}}{E_{AP}} \times \frac{E_{AP}}{E_{gaso}} \times \frac{E_{gaso}}{E_{total}} \times \frac{E_{total}}{G} \times \frac{G}{Pop} \times Pop = H \times C \times P \times S_t \times S_o \times E \times D \quad (4-1)$$

where AP, U_{CO_2} , E_{AP} , E_{gaso} , E_{total} , G, and Pop represent the concentration of air pollutants, CO₂ emissions, all pollutants' emissions, gasoline consumption, energy consumption, GDP, and population, respectively.

H refers to the concentration of pollutants per CO₂ emission unit, signifying how much CO₂ emissions add to the concentration of pollutants. H is the combined effect of CO₂ and air pollutants. C represents the CO₂ emissions for each unit of pollutant released, serving as a measure for the combined reduction of CO₂ and air pollutants.

H and C are regarded as the co-effect of CO₂ and air pollutants collectively. There are several prior studies that quantify the synergistic emission effects of pollutants and CO₂ in a similar way [14,39,40]. P is pollutant emission per unit of gasoline, indicating emission intensity, incorporating vehicle emissions management, fuel upgrades, and vehicle upgrades.

S_t represents the proportion of gasoline used in the overall energy usage of the transportation sector, reflecting the fuel configuration, which is linked to the enhancement of the fuel structure metric in transportation.

S_o refers to the amount of energy used per GDP unit in the transportation sector, reflecting the intensity of energy consumption in this sector.

E is the per capita GDP, signifying the economy's growth. D symbolizes the population and is indicative of the impact of demographic shifts.

In this study, the variable o represents the starting year, and t represents the ending year. The symbols ΔH , ΔC , ΔS_o , ΔS_t , ΔE , ΔP , and ΔD denote the contribution rates of each factor between the starting year and the ending year, respectively. These rates, from left to right,

correspond to the contribution rate of AP per unit of CO₂, the contribution rate of CO₂ per unit of AP, the contribution rate of the energy structure in the transportation sector, the contribution rate of emission intensity in the transportation sector, the contribution rate of per capita GDP, and the contribution rate of population size.

Thus, the LMDI decomposition formula can be expressed as in Equation (4-4). Furthermore, the calculation steps for understanding the contribution of each factor for each province are shown below. A positive final decomposition result for a driving factor indicates its contribution to the overall increase or decrease in air pollutant emissions, while a negative result signifies that the factor drives a change opposite to the general trend. In this study, the LMDI analysis results at both the national and regional scales aggregate the contributions from the provincial level.

$$\begin{aligned}
 \Delta AP &= AP^t - AP^o = \Delta H + \Delta C + \Delta P + \Delta S_o + \Delta S_t + \Delta E + \Delta D \\
 &= \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{H^t}{H^o} \right) + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{C^t}{C^o} \right) + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{P^t}{P^o} \right) + \\
 &\quad \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{S_o^t}{S_o^o} \right) \\
 &\quad + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{S_t^t}{S_t^o} \right) + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{E^t}{E^o} \right) + \frac{AP^t - AP^o}{\ln AP^t - \ln AP^o} \times \ln \left(\frac{D^t}{D^o} \right)
 \end{aligned} \tag{4-4}$$

4.4.4. Regional Variability Analysis

There are obvious inter-regional differences in the synergistic emission effects of VOC, NO_x, and CO₂, which may be due to a variety of factors. To assess and compare both inter- and intra-regional disparities, we selected the Theil index as our measurement tool. The Theil index is a special form of the generalized entropy (GE) index system [41]. It is a tool used to measure the level of inequality and is widely used in the analysis of regional environmental load, energy consumption, and other fields [42,43]. This index allows for the examination of pollution variation both between and within regions, enabling broad-scale evaluation of

changes in pollution patterns [44]. The Theil index is usually a positive number between 0 and 1, but a negative Theil index is still valid [45].

Based on Shorrocks [46], this study improves the formula for calculating the Theil index from GDP per capita, population density, population size, the total energy consumption of the transportation sector, and the total gasoline consumption of the transportation sector.

$$T_{total} = \sum \frac{y_m}{Y} \times \lg \frac{(\frac{y_m}{Y})}{(\frac{x_m}{X})} \quad (4-5)$$

$$T_{inter} = \sum \frac{y_j}{Y} \times \lg \frac{(\frac{y_j}{Y})}{(\frac{x_j}{X})} \quad (4-6)$$

$$T_{intra} = \sum \frac{y_m}{Y} \times \lg \frac{(\frac{y_j}{Y})}{(\frac{x_m}{y_j})} \quad (4-7)$$

In these equations, T_{total} represents the overall national Theil index and T_{inter} implies the inter-regional Theil index. T_{intra} indicates the intra-regional Theil index. y_m is the cumulative amount of synergistic emission reductions in a province, and y_j is the cumulative amount of synergistic emission reductions in a region. Y denotes cumulative, nationally coordinated emission reductions. x_m denotes GDP per capita, population density, population size, the total energy consumption of the transportation sector, and the total gasoline consumption of the transportation sector in a given province. x_j denotes the GDP per capita, population density, population size, the total energy consumption in the transportation sector, and the total gasoline consumption of the transportation sector of one region. X signifies the GDP per capita, population density, population size, the total energy consumption of the transportation sector, and the total gasoline consumption of the transportation sector across China.

4.3.5. Data

This study collected panel data from 30 Chinese provinces (excluding Tibet, Hong Kong, Macao, and Taiwan). Data on air pollutants, including SO₂, NO_x, CO, VOC, NH₃, PM₁₀, PM_{2.5}, black carbon (BC), organic carbon (OC), and CO₂, from 2001 to 2020 were taken from the MEIC database. Their emissions were estimated from 1800 source categories across 55 sectors and 42 fossil fuel types. Version 1.4 of the MEIC database was chosen for analysis in this study.

Population and gross domestic product (GDP) data, from 2001 to 2020, were sourced from the China Statistical Yearbook. Private car ownership data, from 2001 to 2020, were derived from the Transportation Statistics Yearbook. The total energy consumption and gasoline consumption data, from 2001 to 2020, for the transportation sector were obtained from the China Energy Statistical Yearbook. Specifically, the total energy and gasoline consumption data for the transportation sector in the China Energy Statistical Yearbook 2020 were calculated after converting all types of energy consumption into standard coal equivalents, using the conversion tables provided in the China Energy Statistical Yearbook 2020. The specific conversion coefficients were as follows: crude oil at 1.4286 kg of standard coal per kilogram, fuel oil at 1.4286 kg of standard coal per kilogram, and gasoline and kerosene at 1.4714 kg of standard coal per kilogram. For individual years with missing data, we used linear interpolation based on the data from the nearest available years.

4.5 Results

4.5.1. Emission Trends

The MEIC database classifies the transportation sector into four categories, namely gasoline, diesel, motorcycles, and off-road vehicles, and these categories were used to determine the emissions that were counted. Since there was no significant change in the proportion of each category between 2001 and 2020, this study selected the year 2020 as an optimal example for analysis (Figure 4-2). The most significant emissions from gasoline,

diesel, and off-road vehicles were CO₂, followed by CO and NO_x. In terms of an increasing or decreasing trend for each emission, the transportation sector showed a decreasing trend in all emissions except for CO₂ and NH₃ emissions, which were generally trending upwards (Figure 4-3). The average CO₂ emissions from the transportation sector were 20% from diesel vehicles, 35% from motorcycles, and 41% from off-road vehicles between 2001 and 2020. Motorcycle emissions accounted for most of the expansion between 2001 and 2020, while emissions from off-road vehicles and diesel vehicles gradually shrank after 2015.

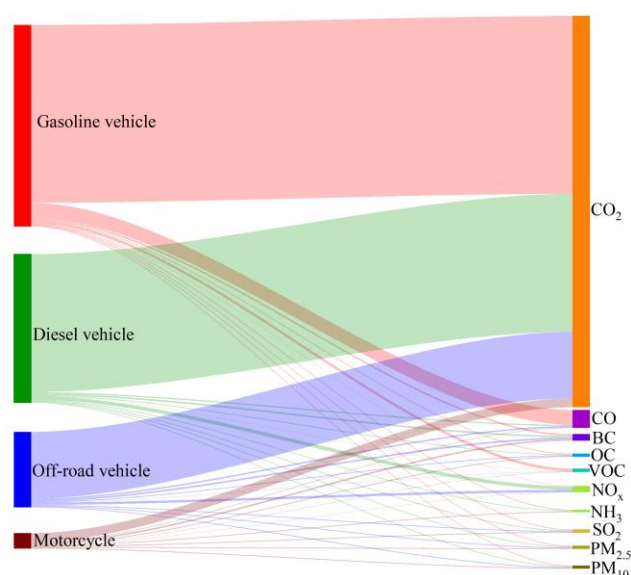


Figure 4-2. Sources of pollutant emissions in 2020. *Note: This diagram depicting the emission pathways from various vehicle categories to multiple air pollutants and carbon dioxide (CO₂). The left-hand side of the diagram represents four major emission sources: gasoline vehicles, diesel vehicles, off-road vehicles, and motorcycles. The right-hand side corresponds to the target pollutants, including CO₂, CO, BC, OC, VOC, NO_x, NH₃, SO₂, PM_{2.5}, and PM₁₀. The width of each colored flow indicates the relative magnitude of emissions from each vehicle type to each pollutant. Similarly, the height of the vertical bars reflects the total proportion each vehicle category contributes to all emissions on the left, and the proportion each pollutant receives from all sources on the right.*

From Table S4-1 (in the Supplementary Materials) and Figure 4-3, we can see that, in 2020, off-road vehicles produced 47–48% of PM (PM_{2.5} and PM₁₀) emissions, while diesel vehicles produced 39% of PM emissions. Between 2001 and 2020, the percentage of off-road

PM_{2.5} and PM₁₀ emissions nearly doubled, from 35% to 63% and 36% to 64%, respectively. Regarding the 20-year average, OC emissions totaled 44% from off-road vehicles and 35% from diesel vehicles, while BC emissions totaled 51% from off-road vehicles and 20% from diesel vehicles. Meanwhile, off-road vehicles accounted for 61% and 69% of 2020 emissions for OC and BC, respectively. In 2001, the SO₂ emissions from diesel vehicles and off-road vehicles were 34% and 40%, respectively. In 2020, SO₂ emissions from diesel vehicles reached 18%, while SO₂ emissions from off-road vehicles increased to 63%. In summary, the proportion of off-road vehicles in the six emission categories of CO₂, PM_{2.5}, PM₁₀, OC, BC, and SO₂ has expanded, and the reduction of off-road vehicle emissions will become a priority in the field of transportation in the future. Based on the 20-year average, gasoline vehicles accounted for 77% of CO emissions, 69% of VOC emissions, and 68% of NH₃ emissions, respectively. This suggests that the management of gasoline vehicles and the continuous upgrading of fuels continue to play an important role in reducing emissions.

This study took the previous year's data as the base year and calculated the annual rate of change in the data (Figure 4-4). The results showed a general downward trend in energy consumption in the transportation sector, in gasoline consumption, and in the growth rate of private vehicles. However, the growth rate of private vehicles is still positive, and the total volume is increasing. The growth rates of CO₂ and air pollutants emitted by the transportation sector are negative, which indicates a downward trend in emissions. In terms of the degree of change in the average annual rate, gasoline consumption and total energy consumption in the transportation sector changed dramatically between 2002 and 2008, then stabilized and subsequently showed a decreasing growth rate after 2009. This was due to the establishment of the Ministry of Transport of the People's Republic of China (MOT) by the government in 2008. The MOT formulated two standards, namely "Fuel Consumption Limits and Measurement Methods for Operating Passenger Vehicles" and "Fuel Consumption Limits and Measurement Methods for Operating Freight Vehicles". These policies enabled the implementation of the Energy Law of the People's Republic of China, which was amended and put into effect in 2009. In 2013, China implemented the carbon emissions trading market and the Air Pollution Prevention and Control Action Plan (APAP). This included the strict

control of motor vehicles, such as the release of the National IV and National V stages of automotive diesel standards (Table S4-2 in the Supplementary Materials), accelerating the elimination of yellow-labeled vehicles (vehicles classified as yellow-labeled include gasoline vehicles failing to comply with National I emission criteria and diesel vehicles with emissions falling short of National III standards) and old vehicles. In 2013, 17 provinces introduced subsidies for the elimination of yellow-labeled vehicles [47]. As a result, the transportation sector saw a significant reduction in energy consumption, gasoline consumption, and CO₂ emissions. Therefore, when comparing the synergistic effect as well as changes in emission intensity in Section 4.4.3, this paper chose to compare 2013 and 2020.

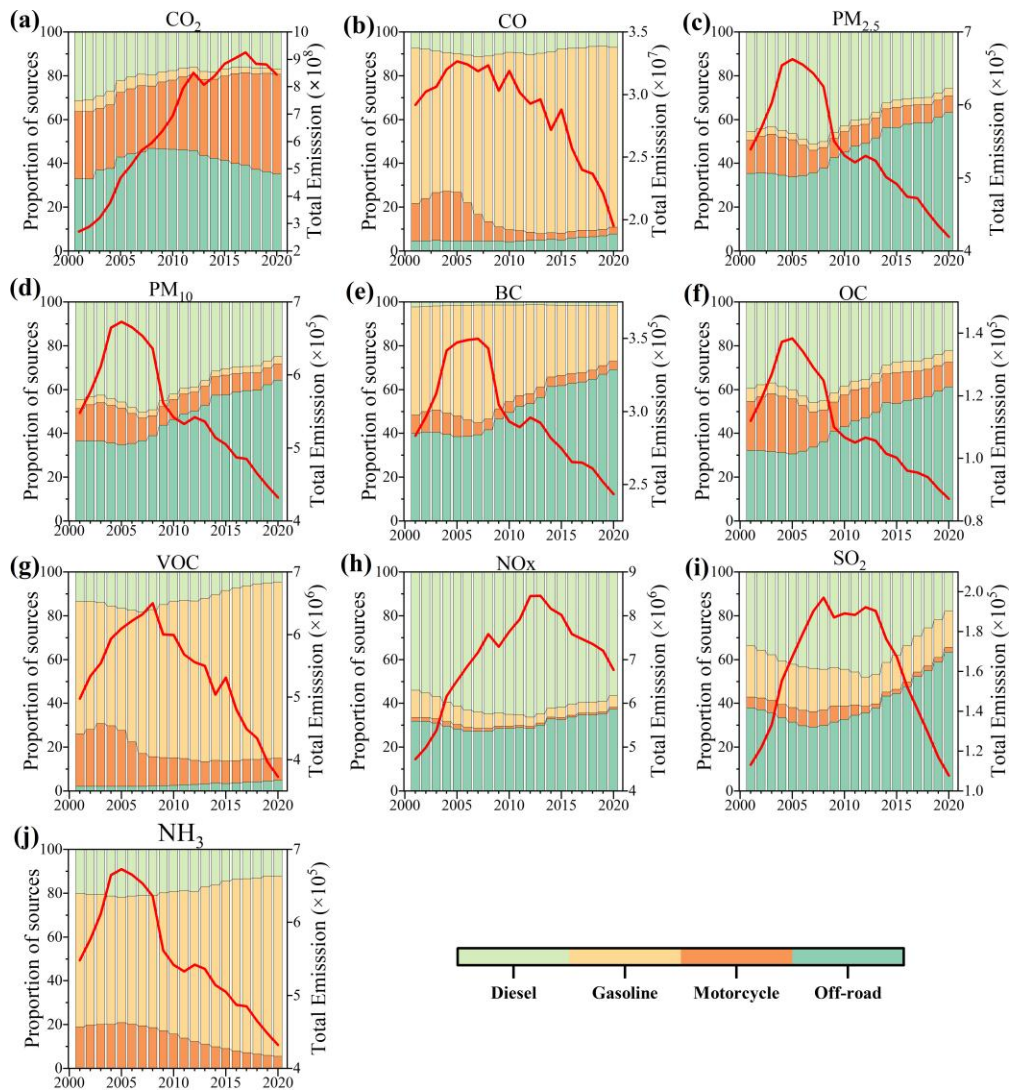


Figure 4- 3. Sources of pollutants and changes in emissions. *Note: The subfigures (a- j) show sources of CO_2 , CO, $\text{PM}_{2.5}$, PM_{10} , BC, OC, VOC, NOx, SO_2 , NH_3 , separately.*

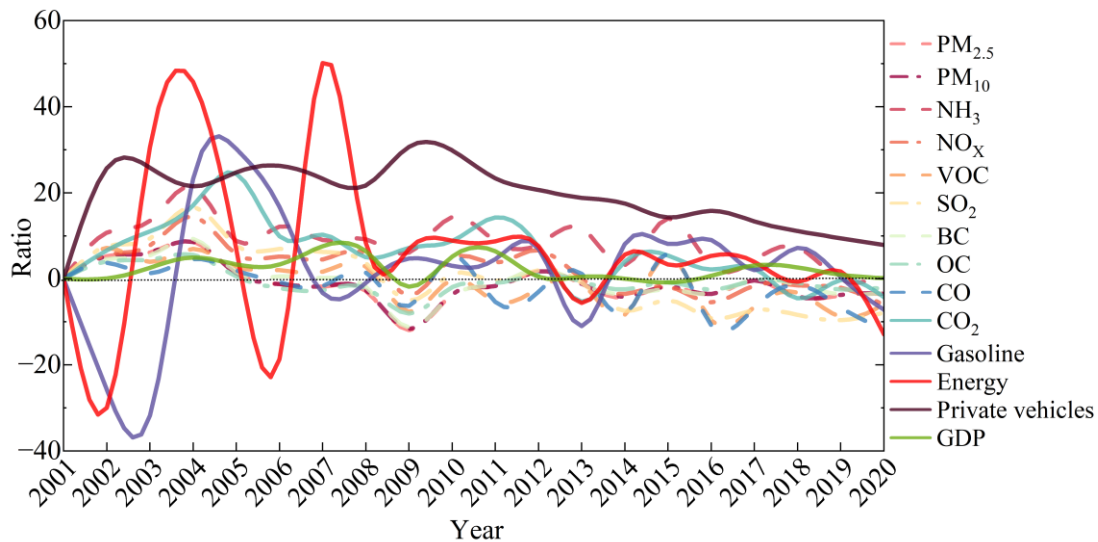


Figure 4-4. Changes relative to the previous year.

4.5.2. Characterization of Pollutant Emissions from the Transportation Sector

This study calculated the cumulative effect of each factor on pollutant emissions from 2002 to 2020 (Table 4-2). H indicates that, for every additional ton of CO₂ emissions, the emissions were reduced by 0.286 tons for VOC, by 0.285 tons for NO_x, by 0.044 tons for PM_{2.5}, by 0.044 tons for PM₁₀, by 2.845 tons for CO, and by 0.009 tons for SO₂. C indicates that each increase of 1 ton for VOC, NO_x, PM_{2.5}, PM₁₀, CO, and SO₂ emissions resulted in 5246.998 tons, 2099.827 tons, 52,246.265 tons, 50,683.282 tons, 1055.803 tons, and 198666.364 tons of CO₂ emissions, respectively. H+C is the synergistic effect of pollutants with CO₂, and there is a significant positive value for the ratio of VOC, PM_{2.5}, SO₂, and CO₂ emissions. This suggests a significant synergistic effect of CO₂ and air pollution in the transportation sector. P indicates pollutant emissions per unit of gasoline, which gives the emissions intensity and represents the outcome of vehicle emissions management, fuel upgrades, and vehicle upgrades. VOC emissions decreased by 36,091.316 tons, NO_x by 32,005.966 tons, PM_{2.5} by 3900.931 tons, PM₁₀ by 39,190.003 tons, CO by 251,946.874 tons, and SO₂ by 644.893 tons between 2020 and 2020. This shows that vehicle management, as

well as upgrades for the transportation sector, can help to reduce pollutant emissions. St indicates the share of gasoline in all energy consumption by the transportation sector, which suggests an energy mix in the transportation sector. Changes in the energy mix have served to reduce air pollutants over the last 20 years; however, its reduction value is smaller than that of P (Rows St and P in Table 4-2). S_o refers to energy consumption in the transportation sector per unit of GDP, indicating the energy consumption intensity in the transportation sector, a factor that contributes to pollutant emissions. E indicates that the cumulative effect of GDP per capita on the emission of each pollutant is 8.44, which is significantly larger than that of GDP. Finally, D indicates that the cumulative effect of population size on the emission of each pollutant is 14331.66, which is larger than that of the GDP, indicating that the size of the population results in larger pollutant emissions.

Table 4- 2. Impact on pollutant emissions.

	VOC	NO _x	PM _{2.5}	PM ₁₀	CO	SO ₂
H	-0.286	-0.285	-0.044	-0.044	-2.845	-0.009
C	5246.998	2099.827	52,246.265	50,683.282	1055.803	198,666.364
P	-36,091.316	-32,005.966	-3900.931	-3919.003	-251,946.874	-644.893
St	-3.303	-3.303	-3.303	-3.303	-3.303	-3.303
S_o	4.174	4.174	4.174	4.174	4.174	4.174
E	8.440	8.440	8.440	8.440	8.440	8.440
D	14,331.660	14,331.660	14,331.660	14,331.660	14,331.660	14,331.660

Note: $H = \frac{AP}{U_{co2}}$, $C = \frac{U_{co2}}{E_{AP}}$, $P = \frac{E_{AP}}{E_{gaso}}$, $St = \frac{E_{gaso}}{E_{total}}$, $S_o = \frac{E_{total}}{G}$, $E = \frac{G}{Pop}$, $D = Pop$.

4.5.3. Distribution of Synergistic Effects and Changes

This study analyzed the seven factors listed in Table 4-2 that affect pollutant emissions. Three of the factors, H, C, and P, demonstrate different regional differences depending on the pollutants. As explained previously, P denotes air pollutants emitted per unit of gasoline and refers to the emission intensity of the transportation sector. Figure 4-5 displays the

emission intensity on the horizontal axis and the synergistic effect of the pollutant with CO₂ on the vertical axis, while the red dots mark the average of the 30 provinces. Xinjiang is not included in the figure because its emission intensity is much higher than the national average. The figure divides the 29 provinces into four quadrants, with the first quadrant indicating a high emission intensity in the transportation sector and a high synergistic effect. The second quadrant indicates that the transportation sector has a low emission intensity and a high synergistic effect. The third quadrant indicates that the transportation sector has a low emission intensity and a low synergistic effect. Quadrant 4 indicates that the transportation sector has a high emission intensity and a low synergistic effect. The overall view of the scatter plot distribution shows a tendency for provinces to move from the third and fourth quadrants (2013) to the second quadrant (2020). The red dots on the graph (representing the averages) clearly exhibit a trend towards the upper left (2020), departing from the lower left (2013). In terms of changes in the distribution of specific provinces, Beijing, Tianjin, and Shanghai clearly fit the overall trend and were expected to move to the fourth quadrant in 2020 (except for Tianjin's CO). In contrast, Hebei showed a countertrend movement; that is, it moved from the third quadrant or from near the third quadrant to the fourth quadrant. In 2020, Beijing showed a high synergy of air pollutants and CO₂ emissions, while Hebei became the province with the highest pollutant emissions per unit of gasoline in the country. It is also possible to note that Shandong and Liaoning appeared to move in opposite directions. We compared the emission sources of these four provinces and found that Shandong, Liaoning, and Hebei have different pollutant emission structures (Figure 4-6).

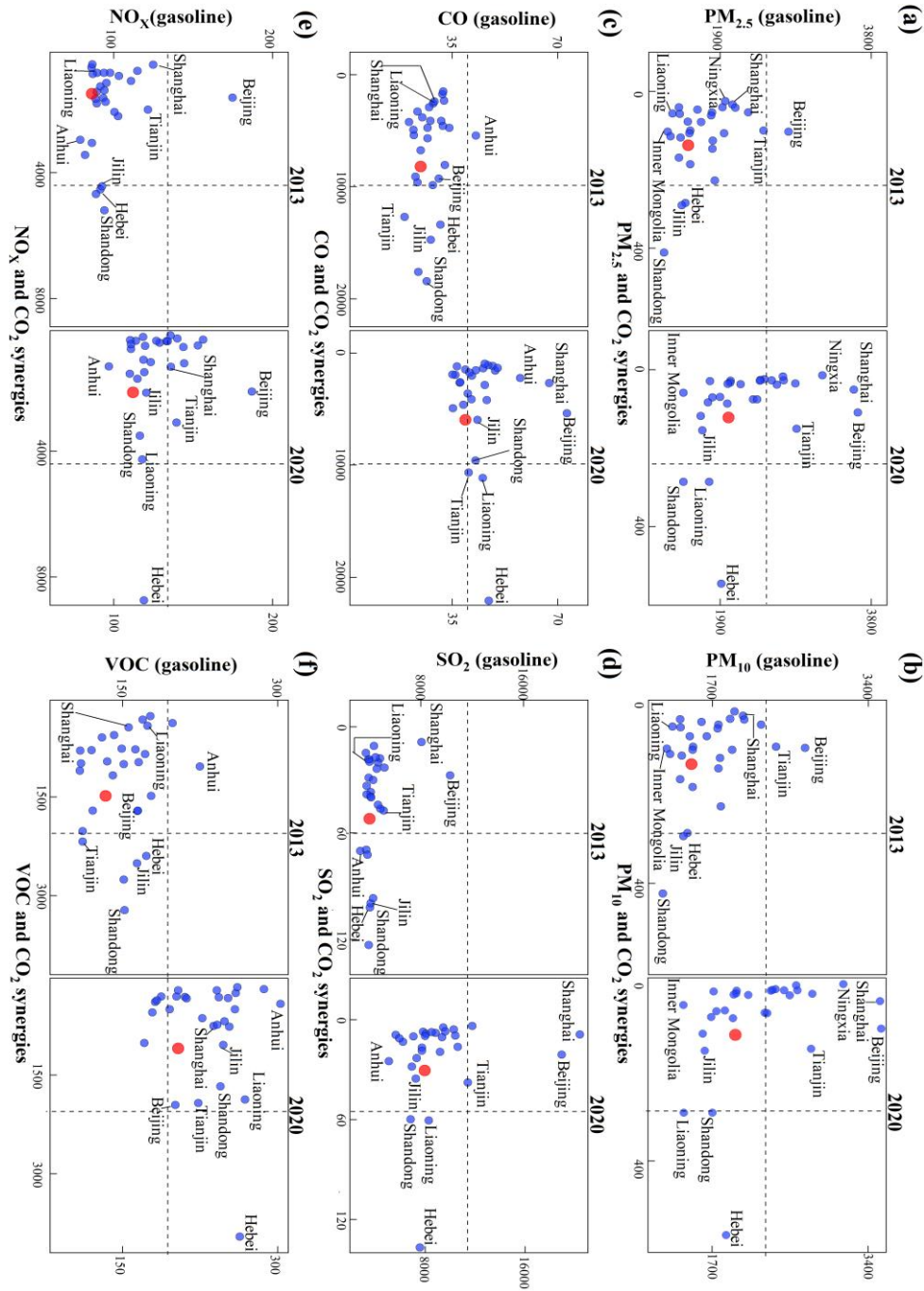


Figure 4- 5. Emission intensity and synergistic effects in 2013 and 2020. *Note: The subfigures (a-f) show synergistic effect of the pollutant with CO₂. The red dots mark the average of the 30 provinces. The horizontal coordinates represent synergies, while the vertical coordinates indicate emission intensities. The data are derived from LMDI decomposition results and are presented without units.*

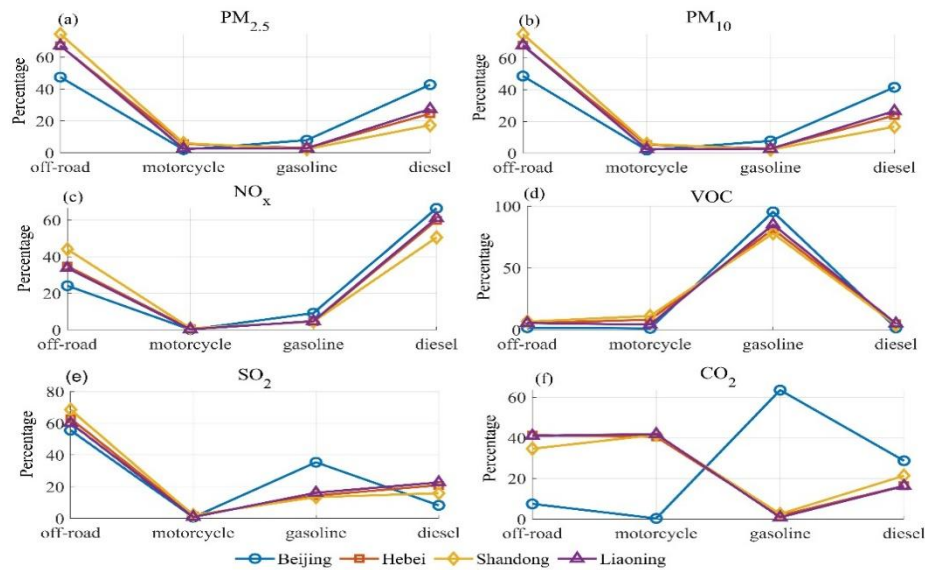


Figure 4- 6. Variations in emission origins across four provinces. *Note: The subfigures (a-f) show sources of PM_{2.5}, PM₁₀, NO_x, VOC, SO₂, CO₂, separately.*

To be specific, more than 60% of PM_{2.5} and PM₁₀ emissions originated from off-road traffic, more than 50% of NO_x emissions originated from diesel vehicles, more than 70% of VOC emissions originated from diesel vehicles, more than 60% of SO₂ emissions originated from off-road vehicles, and 70% of CO₂ emissions came from motorcycles and off-road vehicles in Shandong, Liaoning, and Hebei. In addition, 63% of Beijing's transportation sector's CO₂ emissions originated from gasoline vehicles. In short, off-road vehicles, on-road diesel vehicles, and motorcycles were the main sources of emissions in these provinces. Recently, Hebei, for the first time since the promulgation of the Hebei Provincial Motor Vehicle Pollution Prevention and Control Methods in 2012, introduced motor vehicle-related regulations on 10 April 2020 [48], namely the "Hebei Provincial Motor Vehicle and Non-Road Vehicle Mobile Machinery Emission Pollution Management Regulations" and the "Hebei Provincial Motor Vehicle and Non-Road Vehicle Mobile Machinery Emission Pollution Management Regulations". Hebei province banned the use of National III and non-National III diesel vehicles at the end of 2020 [49].

4.5.4. Differential Analysis of the Seven Regions

After analyzing the impact of various factors on pollutant emissions, it was found that there were significant regional differences in synergistic emission reductions. This section focuses on analyzing the reasons for the formation of regional variability.

Based on the Kaya equation and Equation (4-3) in this study, five factors were selected: population, population density, GDP per capita, total gasoline consumption of the transportation sector, and the total energy consumption of the transportation sector. The inequality index for each region was measured using the Theil index (Table S4-4 in the Supplementary Materials). In Figure 4-6, VOC-Pop represents the Theil index of VOC and CO₂ synergistic emission reductions based on the population size, and VOC-Ga represents the Theil index of VOC and CO₂ synergistic emission reductions based on the gasoline consumed in the transportation sector. The results of the calculations show that gasoline consumption in the transportation sector in each region had the highest Theil index. This means that, at this stage, gasoline consumption is the main cause of regional differences in synergistic emissions in the transportation sector in China.

Figure 4-7 shows the Theil index for each pollutant, calculated based on population and gasoline consumption, except for VOC and NO_x, for which there are large differences in the Theil index. The inequality indices for the other pollutants showed a smaller difference and even a higher population-based Theil index than gasoline consumption-based Theil indices between 2001 and 2006. In summary, the inequality indices for the five pollutants combined showed that gasoline consumption in the transportation sector created greater inequality in synergistic emission reductions between regions. Moreover, the study calculated that the gap in synergistic emissions due to gasoline consumption was mainly caused by inter-regional differences (Table S4-4-b in the Supplementary Materials), with intra-regional differences remaining above and below zero—a much smaller value than for the inter-regional Theil index.

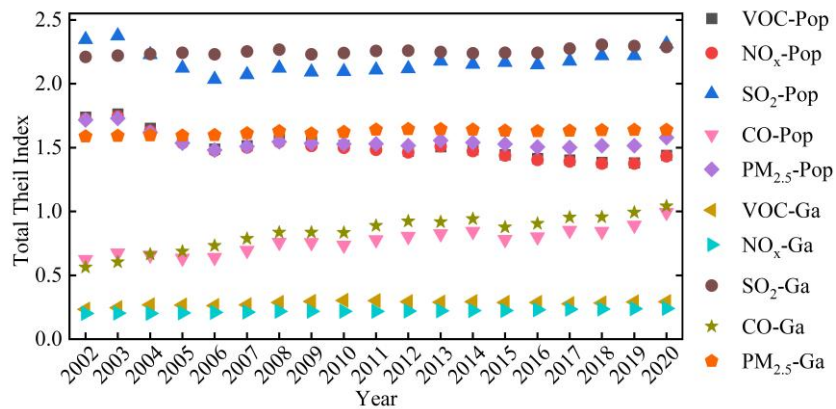


Figure 4-7. Theil index with population and gasoline as the base.

4.6 Discussion and Policy Recommendations

Seven pollutant emission impact factors were obtained using the Kaya equation and the LMDI method. These factors are listed in descending order according to the magnitude of their impact on reducing pollutant emissions, as follows: pollutant emission intensity in the transportation sector, energy mix in the transportation sector, air pollution accompanied by carbon dioxide emissions, energy consumption intensity in the transportation sector, GDP per capita, total population, and carbon dioxide emissions accompanied by air pollution (Table 4-2). Based on the results of the above analysis, the following recommendations are made, considering the current transportation situation in China.

4.6.1. Homogeneity Factor Analysis

Of the seven factors listed above, the sum of air pollution accompanying CO₂ emissions (H in Table 4-2) and the sum of CO₂ emissions accompanying air pollution (C in Table 4-2) are thought to have a synergistic effect. Four of the five remaining components (St, So, E, and D in Table 4-2) are consistent across regions. In addition to the transportation energy mix (St in Table 4-2), which reduces emissions, the other three factors, energy consumption

in the transportation sector (So in Table 4-2), GDP per capita (E in Table 4-2), and population (D in Table 4-2), all contribute to emissions. Over the past 20 years, the impact of total population size on transportation pollutant emissions has been significantly larger than that of per capita GDP, the energy mix of the transportation sector, and the intensity of energy consumption in the transportation sector. At the same time, improvements in the transportation system [50] will increase the population of an area. At present, China is still in a period of continuous development of transportation networks. In 2021, the Chinese government formulated an ambitious “14th Five-Year Plan (2021–2025)” for the development of a modern comprehensive transportation system, setting the goals of doubling the mileage of high-speed railroads in operation, covering more than 95% of cities with a population of more than one million, covering more than 98% of cities with a population of more than 200,000 with expressways, and covering approximately 92% of prefecture-level cities using civil transportation airports. Along with the expanding transportation network, the pressure on pollution control and CO₂ emission reductions during the construction and operation of transportation infrastructure has also increased.

Previous research has indicated that the high concentration of the population in urban areas [15] can lead to a decrease in the overall cost of natural monopolies, such as electricity, gas, liquefied petroleum gas, natural gas, and public transportation, thereby encouraging residents to use more clean energy and public transportation services, which, in turn, lowers pollutant emissions and enhances the air quality. However, the current urban population density in China is decreasing [51]. Similarly, CO₂ shows a nonlinear relationship with population density [52], and the effect of carbon emission reduction resulting from increasing urban density is greatest in medium-sized cities (with a population of more than 500,000 and less than 1 million). An increase in urban density to a medium level provides the most significant reduction in carbon emissions, followed by large cities with a population below 5 million. In contrast, megacities with over 5 million inhabitants fail to demonstrate a significant carbon reduction effect due to urban density. Therefore, policymakers should formulate plans to reduce the demand for transportation and thus reduce emissions, considering the different demographics of different provinces.

4.6.2. Heterogeneity Factor Analysis

Of the seven pollutant emission impact factors obtained from the Kaya equation and the LMDI model, the synergistic factor H+C and the emission intensity of the transportation sector are heterogeneous, and their analysis is presented in Section 4.5.1. of this article. Section 4.5.2. attempts to analyze the reasons for the existence of heterogeneity. Based on the above analysis, the following observation was made: At this stage, there is a synergistic effect between CO₂ and air pollution in China's transportation sector, with Beijing having the best synergistic effect. Figure 6 shows that Beijing's PM and SO₂ emissions are mainly from off-road transportation (including aviation and railroads), while NO_x, VOC, and CO₂ emissions are mainly from gasoline and diesel vehicles. Clean energy substitutions for road vehicles and aviation, as well as the electrification of railroads, offer the best potential for synergistic emission reductions [53].



Figure 4-8. Traditional geographical classification.

This study divided the provinces in China into seven regions (Figure 4-8), and the synergistic effect is evident in all regions. However, there is a difference in the distribution

of the effect, which is mainly due to the difference in the total amount of gasoline consumed in different regions. After comparing the emission sources in the seven regions (Figure 4-9), it was found that particulate matter emissions from the transportation sector in southern China are mainly from off-road vehicles and diesel vehicles, while more than 50% of the particulate matter emissions in the other six regions of China are from off-road vehicles. This suggests that the management of diesel vehicles, emission monitoring, and energy-upgrading measures need to be strengthened in the three southern provinces of China, namely Guangdong, Guangxi, and Hainan. A case study made a similar suggestion for the transportation sector in Guangdong province [54]. It was emphasized that the most effective approach to achieving long-term synergistic benefits is to optimize the energy mix and replace fossil fuels with electricity, hybrids, and other environmentally friendly energy sources. This approach will lead to significant reductions in both air pollutant emissions and CO₂ emissions.

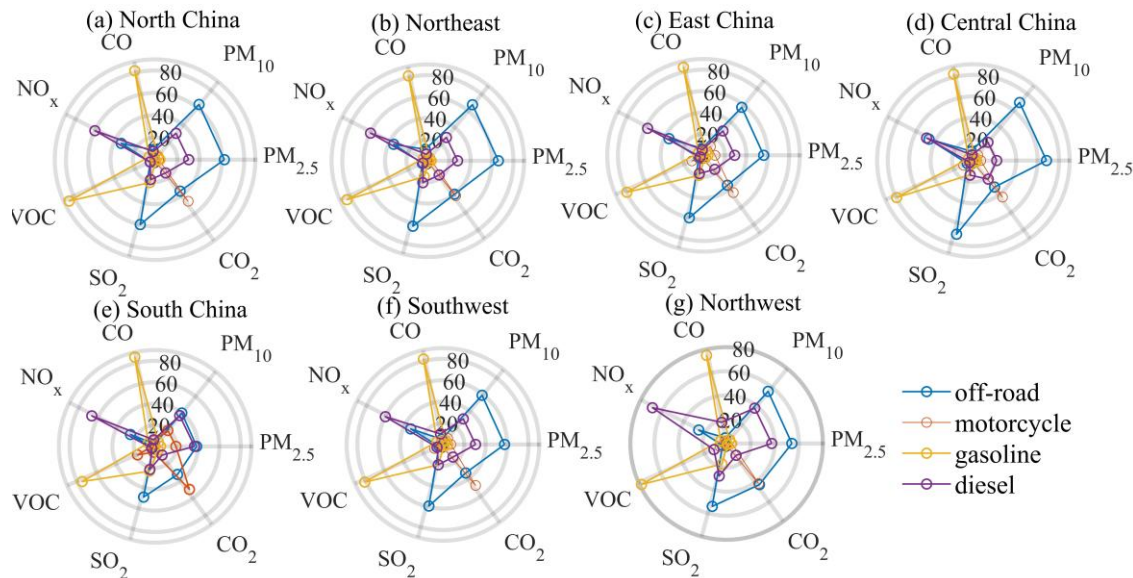


Figure 4-9. Emission origins of the seven major regions.

NO_x emissions in Central China are mainly from off-road vehicles and diesel vehicles (Figure 4-9); this is very different from other regions, where more than half of the emissions are from diesel vehicles. This suggests that Henan, Hubei, and Hunan need to strengthen the use of gasoline for off-road vehicles and diesel vehicles. Similar results were obtained in a previous study [55] that analyzed emissions in Henan province and identified CO, NO_x, VOC, and CO₂ emissions (compared to Central China in Figure 4-9) as originating from on-road vehicles and SO₂ emissions as originating from off-road vehicles. Areas with significant levels of NO_x and VOC emissions are typically located near railroad trunk lines and industrial centers that have substantial transportation requirements. Improving transportation systems may result in a synergistic reduction in emissions. It is essential to prioritize the promotion of clean energy and the use of new energy vehicles in the long term.

4.5.3. Limitations and Future Research

This study used carbon emission and air pollution data from the MEIC database to maintain consistency between the datasets; therefore, the analysis could only evaluate at the provincial level and failed to consider the specifics of transportation at the municipal level.

The results show that pollutant emissions from the transportation sector in China have generally decreased, whereas CO₂ emissions continue to increase. This study examined the synergistic effect between pollutant emissions and CO₂, using pollutant emissions as the disaggregation target, and concluded that population size is a determining factor. However, this study did not examine the synergistic effect of carbon dioxide as a decomposition target.

This study employed a commonly utilized geospatial clustering method to categorize regions into seven major areas. However, pollution emissions from the transportation sector are closely intertwined with the patterns of inter-regional movement of people and goods, the optimization and improvement of transportation networks, and varying transportation structures across different regions, such as the development of public transportation [56] and

the growth of electric vehicles [57]. These aspects present a broad horizon for future research endeavors.

4.7 Conclusions

This study analyzed whether there are synergistic effects of carbon dioxide and air pollutants in the transportation sector and investigated the driving factors behind pollutant emissions, the role played by each factor, and whether there are regional differences in synergistic effects. The main findings are as follows:

1. Air pollutants emitted by the transportation sector in China display a downward trend. Total carbon dioxide emissions, on the other hand, have continued to increase. The proportion of emissions from off-road vehicles is also increasing.
2. Over the past two decades, a synergistic relationship has emerged between CO₂ emissions and air pollution in China's transportation sector. Optimizing this sector's energy mix can significantly lower air pollution, as reflected in emission intensity, which measures the impact of vehicle emission management, fuel quality improvement, and vehicle technology upgrades. Additionally, transportation emissions driven by population growth now exceed those linked to per capita GDP.
3. From 2013 to 2020, the transportation sector in China reduced its emission intensity and increased its synergy, with Beijing showcasing the highest synergistic effect. Shandong, Liaoning, and Hebei exhibited varying trends, with 70% of their CO₂ emissions stemming from motorcycles and off-road vehicles compared to 63% of CO₂ emissions originating from gasoline-powered vehicles in Beijing. Regional differences in effect distribution are attributed to variations in gasoline consumption. In southern China, particulate matter emissions primarily originate from off-road and diesel vehicles, while in other regions, off-road vehicles account for over 50% of emissions.
4. Henan, Hubei, and Hunan should enhance their management of off-road and diesel vehicles, while Guangdong, Guangxi, and Hainan should focus on controlling

diesel vehicle emissions. Policymakers should create development plans according to the population sizes of provinces in order to decrease transportation demand and reduce pollutant emissions.

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Supplementary Materials
Appendix Table S4-1 Proportion of emission sources

Category	Year	Off-road	Motorcycle	Gasoline	Diesel
CO ₂	2001	33	31	5	31
	2020	35	45	2	17
	Average 20-year	41	35	4	20
CO	2001	5	17	71	7
	2020	8	3	82	7
	Average 20-year	5	9	77	9
PM _{2.5}	2001	35	15	4	45
	2020	63	8	3	26
	Average 20-year	47	11	3	39
PM ₁₀	2001	36	15	4	45
	2020	64	7	3	25
	Average 20-year	48	11	3	39
BC	2001	40	8	49	2
	2020	69	4	25	2
	Average 20-year	51	6	41	2
OC	2001	32	23	6	39
	2020	61	11	5	22
	Average 20-year	44	17	5	35
VOC	2001	2	24	60	14
	2020	5	10	80	5
	Average 20-year	3	16	69	12
NO _x	2001	32	2	12	54
	2020	37	1	5	56
	Average 20-year	31	1	7	61
SO ₂	2001	38	5	23	34
	2020	63	2	16	18
	Average 20-year	40	4	18	38
NH ₃	2001	0	19	61	20
	2020	0	5	82	12
	Average 20-year	0	14	68	18

Appendix Table S4-2 Fuel upgrade timeline

Year (2003 to 2020)	03-05	06-09	10	11	12	13	14	15	16	17	18	19	20
Automotive gasoline	I	II	III			IV				V		VI	
Automotive diesel	I				III			IV			V		VI
Regular diesel	I						III			IV	V	—	

Note: Roman numerals indicate the number of grades corresponding to the Chinese fuel standard

Appendix Table S4-3 Sector Categories used in the article.

Transport	Fishing	Off-road mobile source	Off-road mobile source
	International aviation		
	Domestic aviation		
	Rail		
	International navigation		
	Domestic navigation		
	Pipeline transport		
	Other non-specified transport		
	Agriculture and forestry	On-road mobile source	Diesel vehicles
	Cars		
	Light duty trucks		Gasoline vehicles
	Buses		
	Heavy duty trucks		Motorcycles
	Other fleet totals		
	Motorcycles		

Appendix Table S4-4 Theil index**S4-4-a**

Gasoline		VOC	NO _x	SO ₂	CO	PM _{2.5}
Total Theil index	2001	1.7178	1.6918	2.3302	0.603	2.3174
	2002	1.7403	1.7221	2.3456	0.6225	1.716
	2003	1.7634	1.7433	2.3742	0.6735	1.7302
	2004	1.6511	1.6287	2.2284	0.6579	1.6185
	2005	1.5535	1.5357	2.123	0.6331	1.5366
	2006	1.4886	1.4772	2.0344	0.6397	1.4805
	2007	1.5154	1.5014	2.0716	0.6945	1.509
	2008	1.5749	1.5441	2.1215	0.7573	1.546

	2009	1.5473	1.5127	2.0924	0.7547	1.5333
	2010	1.5177	1.4983	2.0962	0.7347	1.5283
	2011	1.5027	1.4829	2.1074	0.7781	1.5299
	2012	1.4732	1.4622	2.1187	0.8042	1.5158
	2013	1.5067	1.5085	2.1764	0.8254	1.5567
	2014	1.4821	1.4725	2.1535	0.8435	1.5406
	2015	1.4431	1.4381	2.1681	0.7803	1.527
	2016	1.4148	1.4037	2.1484	0.801	1.5061
	2017	1.4038	1.3915	2.1768	0.8507	1.5009
	2018	1.3852	1.3744	2.2194	0.8435	1.5146
	2019	1.3813	1.3739	2.2209	0.8918	1.5146
	2020	1.4404	1.4322	2.3109	0.9926	1.5789

S4-4-b

Population Density		VOC	NO _x	SO ₂	CO	PM _{2.5}
Total Theil index	2001	0.2309	0.2011	2.2395	0.5566	2.1976
	2002	0.2352	0.2011	2.2104	0.5624	1.5866
	2003	0.2457	0.2043	2.2191	0.6033	1.5903
	2004	0.2685	0.2026	2.232	0.664	1.5945
	2005	0.2658	0.2047	2.2431	0.6864	1.5936
	2006	0.2628	0.2092	2.2302	0.7307	1.5976
	2007	0.2692	0.2126	2.2532	0.7854	1.6109
	2008	0.2878	0.2183	2.2666	0.8358	1.6281
	2009	0.2958	0.218	2.23	0.8341	1.6092
	2010	0.3028	0.2178	2.2396	0.8324	1.6219
	2011	0.3024	0.2181	2.2567	0.8876	1.6397
	2012	0.2933	0.2196	2.259	0.9219	1.6428
	2013	0.2894	0.2221	2.2483	0.917	1.6432
	2014	0.2936	0.2244	2.2383	0.9418	1.6394
	2015	0.2879	0.2248	2.2421	0.8761	1.6312
	2016	0.2869	0.2294	2.2432	0.9049	1.6273
	2017	0.2766	0.2344	2.2757	0.9532	1.6306
	2018	0.2825	0.236	2.3049	0.9553	1.6364
	2019	0.2905	0.2379	2.2959	0.9924	1.6374
	2020	0.2931	0.2413	2.2882	1.0411	1.6374

S4-4-c

Per GDP		VOC	NO _x	SO ₂	CO	PM _{2.5}
Total Theil index	2001	0.1007	0.0623	-1.5789	-0.7471	-1.5813
	2002	0.0980	0.0598	-1.5644	-0.7508	-1.3310
	2003	0.0948	0.0583	-1.5697	-0.7780	-1.3367
	2004	0.0964	0.0518	-1.5878	-0.8125	-1.3515
	2005	0.0857	0.0476	-1.5959	-0.8266	-1.3599

	2006	0.0775	0.0444	-1.5932	-0.8535	-1.3603
	2007	0.0738	0.0389	-1.6204	-0.8865	-1.3787
	2008	0.0735	0.0342	-1.6389	-0.9118	-1.3915
	2009	0.0696	0.0305	-1.6109	-0.9049	-1.3670
	2010	0.0635	0.0247	-1.6295	-0.9080	-1.3744
	2011	0.0546	0.0212	-1.6561	-0.9505	-1.3885
	2012	0.0469	0.0192	-1.6577	-0.9755	-1.3783
	2013	0.0449	0.0187	-1.6505	-0.9746	-1.3684
	2014	0.0442	0.0187	-1.6399	-0.9871	-1.3581
	2015	0.0426	0.0194	-1.6342	-0.9512	-1.3469
	2016	0.0420	0.0219	-1.6299	-0.9713	-1.3458
	2017	0.0385	0.0242	-1.6540	-1.0109	-1.3600
	2018	0.0429	0.0268	-1.6737	-1.0145	-1.3707
	2019	0.0451	0.0273	-1.6724	-1.0406	-1.3712
	2020	0.0440	0.0264	-1.6649	-1.0745	-1.3710

S4-4-d

Energy		VOC	NO _x	SO ₂	CO	PM _{2.5}
Total Theil index	2001	0.2093	0.1841	0.3918	-0.0692	0.4053
	2002	0.0821	0.0597	0.2214	-0.1250	0.0622
	2003	0.0857	0.0510	0.2177	-0.1205	0.0606
	2004	0.1147	0.0793	0.2553	-0.1070	0.0889
	2005	0.0859	0.0586	0.2290	-0.1131	0.0674
	2006	0.0753	0.0530	0.2177	-0.1091	0.0604
	2007	0.0737	0.0528	0.2179	-0.1019	0.0637
	2008	0.0903	0.0565	0.2214	-0.0879	0.0657
	2009	0.0799	0.0470	0.2089	-0.0924	0.0613
	2010	0.0727	0.0444	0.2075	-0.0991	0.0604
	2011	0.0671	0.0447	0.2105	-0.0953	0.0643
	2012	0.0576	0.0434	0.2164	-0.0944	0.0647
	2013	0.0492	0.0428	0.2155	-0.0987	0.0650
	2014	0.0555	0.0417	0.2180	-0.0914	0.0687
	2015	0.0537	0.0411	0.2284	-0.1016	0.0701
	2016	0.0583	0.0440	0.2330	-0.0952	0.0683
	2017	0.0537	0.0445	0.2351	-0.0912	0.0601
	2018	0.0639	0.0466	0.2483	-0.0873	0.0675
	2019	0.0648	0.0480	0.2420	-0.0824	0.0604
	2020	0.0695	0.0506	0.2541	-0.0700	0.0623

S4-4-e

Population		VOC	NO _x	SO ₂	CO	PM _{2.5}
Total Theil index	2001	-1.2139	-1.2022	-1.9987	-0.9163	-1.9653
	2002	-1.3447	-1.3345	-1.9943	-0.9250	-1.6327
	2003	-1.5020	-1.5074	-1.9673	-0.9431	-1.6108
	2004	-1.4059	-1.4179	-1.8566	-0.9366	-1.5201
	2005	-1.2936	-1.3018	-1.7108	-0.8911	-1.4092
	2006	-1.2381	-1.2375	-1.6117	-0.8841	-1.3386
	2007	-1.2567	-1.2550	-1.6446	-0.9242	-1.3639
	2008	-1.2615	-1.2629	-1.6675	-0.9557	-1.3867
	2009	-1.2436	-1.2438	-1.6390	-0.9508	-1.3676
	2010	-1.2335	-1.2314	-1.6267	-0.9412	-1.3576
	2011	-1.2179	-1.2154	-1.6039	-0.9623	-1.3426
	2012	-1.1934	-1.1898	-1.5776	-0.9757	-1.3227
	2013	-1.2479	-1.2433	-1.6508	-1.0144	-1.3827
	2014	-1.2146	-1.2141	-1.6053	-1.0096	-1.3511
	2015	-1.1811	-1.1831	-1.5633	-0.9583	-1.3186
	2016	-1.1453	-1.1493	-1.5053	-0.9522	-1.2788
	2017	-1.1368	-1.1455	-1.5123	-0.9801	-1.2811
	2018	-1.1120	-1.1204	-1.4687	-0.9535	-1.2451
	2019	-1.1131	-1.1195	-1.4460	-0.9661	-1.2332
	2020	-1.1442	-1.1498	-1.4996	-1.0273	-1.2802

S4-4-f

GASOLINE		VOC	NO _x	SO ₂	CO	PM _{2.5}
Inter-region Theil index	2001	1.7688	1.7993	2.5260	0.6558	2.7488
	2002	1.8150	1.8348	2.5319	0.6791	2.0717
	2003	1.8369	1.8104	2.4774	0.7081	2.0585
	2004	1.7997	1.7582	2.3856	0.7424	1.9811
	2005	1.6519	1.6364	2.2121	0.6735	1.8407
	2006	1.5504	1.5818	2.1351	0.6465	1.7425
	2007	1.5443	1.6596	2.2536	0.6718	1.8214
	2008	1.5029	1.6345	2.2436	0.6664	1.7664
	2009	1.5174	1.6754	2.3266	0.6745	1.7673
	2010	1.5328	1.7214	2.4043	0.6803	1.7660
	2011	1.5485	1.7189	2.4622	0.7368	1.7354
	2012	1.5382	1.7048	2.4948	0.7729	1.6475
	2013	1.5873	1.7670	2.5765	0.8110	1.6747
	2014	1.6140	1.7604	2.6185	0.8597	1.6661
	2015	1.6385	1.6818	2.6050	0.8324	1.6118
	2016	1.6575	1.6150	2.5684	0.8879	1.5789

	2017	1.7209	1.6373	2.6238	0.9958	1.6345
	2018	1.5781	1.4719	2.4016	0.9470	1.5153
	2019	1.5570	1.4866	2.5077	1.0166	1.5369
	2020	1.7024	1.6528	2.7082	1.2203	1.6839
GASOLINE		VOC	NO _x	SO ₂	CO	PM _{2.5}
Intra-region Theil index	2001	0.2696	0.2336	0.2691	-0.1709	-0.2015
	2002	0.2322	0.2089	0.3021	-0.1593	-0.1234
	2003	0.1589	0.1446	0.3637	-0.1318	-0.0841
	2004	0.1101	0.0994	0.2803	-0.1627	-0.1413
	2005	0.1373	0.1274	0.3011	-0.1481	-0.1315
	2006	0.1360	0.1223	0.2801	-0.1558	-0.1247
	2007	0.1571	0.1421	0.3126	-0.1392	-0.0991
	2008	0.1808	0.1651	0.3327	-0.1252	-0.0795
	2009	0.1854	0.1646	0.3421	-0.1190	-0.0625
	2010	0.1657	0.1587	0.3405	-0.1326	-0.0690
	2011	0.1648	0.1554	0.3581	-0.1271	-0.0573
	2012	0.1589	0.1570	0.3731	-0.1304	-0.0606
	2013	0.1367	0.1382	0.3544	-0.1510	-0.0763
	2014	0.1376	0.1304	0.3567	-0.1466	-0.0669
	2015	0.1319	0.1318	0.3855	-0.1543	-0.0767
	2016	0.1329	0.1346	0.4028	-0.1495	-0.0718
	2017	0.1234	0.1247	0.4066	-0.1580	-0.0931
	2018	0.1439	0.1478	0.4843	-0.1466	-0.0590
	2019	0.1400	0.1459	0.4815	-0.1392	-0.0629
	2020	0.1408	0.1522	0.5125	-0.1265	-0.0468

Chapter 5

CONCLUSION

Chapter 5

CONCLUSION

5.1 Main Findings

Since the implementation of the Three-Year Action Plan for Winning the Blue-Sky Protection Campaign and the 14th Five-Year Plan, the transportation and residential sectors have increasingly become key targets of environmental governance, with a significant rise in the frequency of related policy measures. Emission sources in the transportation sector exhibit high regional mobility and structural complexity, involving multiple variables such as vehicle type, usage intensity, and fuel composition. In contrast, emissions from the residential sector are more strongly influenced by individual behavior and display pronounced regional heterogeneity, with notable issues related to decentralized heating and the use of biomass fuels. These characteristics introduce substantial uncertainties and spatial disparities in the effectiveness of governance measures under the current policy framework.

This study employs econometric and energy economics models to quantify both the effects of policies and the priority order of their implementation. Based on an understanding of the spatial impacts caused by these policies, the study further explores the underlying reasons for regional disparities and identifies the driving factors contributing to these differences. Drawing on data from the China Air Quality Online Monitoring and Analysis Platform and the Multi-resolution Emission Inventory for China (MEIC), the study proposes emission reduction strategies that are informed by both spatial and social considerations. The key findings are as follows:

- (1) The 2019–2020 plan did not benefit from expanded policy coverage; Reductions in PM_{2.5} were primarily driven by efforts in less wealthy cities. These cities require

urgent financial support to facilitate industrial upgrading and energy structure optimization.

- (2) Residential emissions mainly originate from coal consumption, while energy emission factors and population size are the primary drivers of pollutant emissions. In the southeast, the synergistic effects are largely influenced by hydropower utilization and the level of urbanization. In the western region, they are more strongly driven by factors such as R&D investment and government governance capacity.
- (3) Population growth has become the primary driver of transportation emissions. Between 2013 and 2020, the synergistic effects steadily increased, with Beijing exhibiting the most significant improvements. Regional differences in synergy are primarily attributed to variations in gasoline consumption patterns.

Chapter 2: This chapter assesses the policy impacts of the autumn and winter air pollution control action plans using panel data and the regression discontinuity design (RDD) method. matters things indicate that the action plans for 2016-2017, 2017-2018, and 2019-2020 have successfully improved air quality, particularly by reducing the concentration of particulate matter such as PM_{2.5}. However, despite the expansion of implementation from 20 to 28 cities in 2017-2018, the overall emission reduction effect was not enhanced. In contrast, the emission reduction effect improved in 2019-2020 with the same number of cities, suggesting that expanding policy coverage does not necessarily enhance policy effectiveness. Consequently, the article does not advocate for further expansion of the policy's scope and instead recommends raising the governance target to mitigate "free rider" behavior. Additionally, a threshold regression model categorizes cities into a "wealthy group" and "less wealthy group." The results demonstrate that air quality is generally superior in wealthy cities; However, the policy's effectiveness during the 2019-2020 period primarily stems from non-affluent cities, which continue to experience high pollution levels and elevated health risks. These cities urgently require increased financial support to facilitate industrial transformation and optimize energy structures.

Chapter 3: The present study seeks to quantify the influence of social factors on the coordinated emission reduction within China's residential sector and to optimize the emission reduction pathway. This is achieved through the application of the LMDI decomposition method in conjunction with the Coordinated Coupling Degree Model with Nested Structures (CCD) and the Geographically Weighted Temporal and Spatial Regression (GTWR) model. The findings indicate that residential emissions predominantly originate from coal consumption, with 12 provinces contributing to over 50% of coal emissions. Energy emission factors and population size emerge as the primary drivers of pollutant emissions. The traditional north-south division is inadequate in accurately reflecting regional differences; thus, this paper proposes a novel regional classification and emphasizes the necessity for targeted policy interventions, such as population control, energy structure optimization, and technological upgrading. Regarding synergistic effects, the degree of coordination is higher in the north compared to the south. In the southeast, hydropower and urbanization levels are the dominant factors, while the west is influenced by R&D inputs, government governance, climate, and other factors. The northeast is more affected by industrial structure and energy consumption patterns. The spatial heterogeneity underscores the importance of developing regional governance strategies tailored to local conditions. The study also reveals that since 2015, population-driven emissions in southern cities have surpassed those in the north for the first time, attributed to rapid urbanization and economic development, thereby establishing them as a new governance.

Chapter 4: This chapter examines the synergistic effects of carbon dioxide and air pollutants within China's transportation sector, systematically exploring the drivers of pollutant emissions, the roles of various factors, and their regional disparities. It is observed that air pollutant emissions from China's transportation sector are generally on a declining trajectory, whereas carbon dioxide emissions continue to rise, with an increasing proportion of emissions originating from off-road vehicles. Over the past two decades, the sector has progressively demonstrated a synergistic relationship between carbon and pollutants, effectively reducing air pollution, particularly through the optimization of the energy mix.

The ongoing decline in emission intensity also reflects the efficacy of vehicle management, fuel quality, and technological advancements. Population growth emerges as the primary driver of transportation emissions growth, surpassing the impact of per capita GDP growth. The synergies increased between 2013 and 2020, with Beijing exhibiting the most significant synergies, while Shandong, Liaoning, and Hebei display different trends due to the high proportion of off-road vehicles and motorcycles. Regional differences in synergies are primarily attributed to gasoline consumption patterns, with particulate matter emissions in the South predominantly arising from off-road and diesel vehicles, whereas off-road vehicles account for more than 50% of emissions in other regions. Consequently, provinces such as Henan, Hubei, and Hunan should enhance the management of off-road and diesel vehicles, while Guangdong, Guangxi, and Hainan should concentrate on controlling diesel vehicle emissions. To improve the efficiency of emission reduction, policymakers should also optimize transport development planning in relation to the population size of each region to reduce travel demand and lower pollution levels.

5.2 Academic Contributions

From the perspective of academic research, the main contributions of this paper are reflected in the following aspects:

Chapter 2 addresses two primary research objectives. Firstly, to address the limitations of existing studies that focus on the 2013-2017 period, this paper evaluates the policy effects of the autumn and winter special actions in 28 joint prevention and control cities during the periods 2017-2018 and 2019-2020, with the aim of determining the current adaptability of the policy. Secondly, considering that social factors such as financial investment in environmental protection, the proportion of the secondary industry, traditional energy use, and economic development have been demonstrated to impact environmental quality, this

paper further investigates whether these factors influence the effectiveness of policy implementation and offers recommendations for the policy's future continuation.

In Chapter 3, this study introduces a dual validation research framework characterized by methodological innovation through the construction of a nested structure that integrates Coordinated Coupling Degree (CCD) and Geographically Weighted Temporal Regression (GTWR), alongside an analysis based on the Log-Mean Divisia Index (LMDI) method. This approach extends the decomposition factors traditionally employed in LMDI, thereby enhancing the robustness of the results through secondary validation. Furthermore, this method facilitates a comprehensive understanding of the intrinsic relationship between the synergistic emission reduction mechanism within the residential sector and social factors, achieving a parametric representation of these social factors while quantifying the synergistic mechanism.

The innovation presented in Chapter 4 is the development of a comprehensive multifactorial model designed to systematically evaluate the synergistic effects of carbon dioxide and air pollutants within the transportation sector, utilizing a "bottom-up" modeling database. This model introduces seven critical variables for quantitative analysis: pollutant-induced CO₂ emissions, pollutant emissions associated with CO₂ emissions, pollutant emission intensity in the transportation sector, energy structure, energy consumption intensity, economic growth level, and population size. Notably, the pollutant emission intensity serves as a novel metric, facilitating cross-sectional comparisons between provinces and cities regarding vehicle and fuel advancements. Furthermore, the quantification of synergies elucidates the connection between CO₂ and air pollution, providing a foundation for a more detailed examination of regional disparities. These findings offer a more scientific and practical basis for formulating emission reduction policies in the transportation sector.

5.3 Future Outlook and Recommendations

During the organization and implementation of this study, several limitations were identified, primarily encompassing the following aspects:

The study presented in Chapter 2 requires further refinement, with particular emphasis on the potential spatial spillover effects of inter-city air pollution. Regarding policy assessment methodologies, the Regression Discontinuity Design (RDD) model is appropriate for evaluating policies with distinct temporal breakpoints, initiatives such as the optimization of the energy structure within the autumn and winter action plans often lack a definitive commencement point and necessitate sustained promotion over an extended period. Consequently, their effectiveness typically becomes evident only after a prolonged duration. Therefore, future policy evaluations should consider both short-term and long-term effects, necessitating further in-depth research in this direction.

In Chapter 3, household survey data led by Tsinghua University is utilized to construct the emission factors of the residential sector in the MEIC database, thereby addressing the limitations of official energy statistics. However, the results exhibit some bias due to variations in survey samples, timing, and methodology, particularly within the rural residential segment. This study employs provincial panel data without incorporating the municipal level, precluding specific assessment of key polluted areas such as the Fenwei Plain for their drivers, which should be addressed in future research. Although the Geographically and Temporally Weighted Regression model elucidates the drivers influencing the coordinated coupling degree, it does not explore the underlying mechanisms in depth. For instance, research and development investment exerts a dampening effect on the synergistic effect in certain provinces, potentially linked to the rebound in industrial energy efficiency, while technological progress has been shown to enhance residential energy efficiency. These findings contribute to understanding the actual impact of social factors on emission reduction and suggest future research directions. Additionally, the applicability of

this model to the transportation sector warrants exploration, given that both residents and the transportation sector are influenced by a combination of behaviors, incomes, and policies.

In Chapter 4, this study utilizes carbon emissions and air pollution data from the MEIC database to ensure data consistency, thereby restricting the analysis to the provincial level and not addressing specific variations in transportation at the municipal level. The findings reveal a reduction in pollutant emissions from China's transportation sector, while carbon dioxide emissions have continued to rise. By employing pollutant emissions as the decomposition target, the study identifies population size as a significant factor influencing the synergistic effect, although it does not further analyze this factor using CO₂ as the target variable. Additionally, while the study categorizes the country into seven regions through geospatial clustering, transportation emissions are influenced by various factors, including cross-regional population and goods movement, transportation network optimization, and regional differences in transportation structure (e.g., public transportation, electric vehicle development). These aspects warrant further exploration in future research.