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When Governance Meets Artificial Intelligence: AI-Enabled Industrial Robotics, Environmental Governance, and Carbon Emissions in context of Chinese provinces

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Abstract

China's decarbonisation puzzle is stark: energy-related CO_2 emissions climbed to about 12.6 Gt in 2023—roughly one-third of the global total—even as industrial automation surged, with 276,288 robots installed that year, the most worldwide. In parallel, environmental governance has been emerged as the key factor to influence the carbon emissions in China. These cross-currents motivate our central question: how do industrial robotic penetration (RBT) and governance efforts, separately and jointly, influence China's provincial carbon trajectories? Using panel data for 30 provinces (2007~2022), we conduct pre-diagnostics for cross-sectional dependence, slope heterogeneity, and serial correlation, then estimate Feasible GLS models as main estimation approach. The baseline results show that higher RBT is associated with lower emissions, consistent with process upgrading and energy-efficient production. By contrast, environmental governance correlates positively with emissions in linear specifications, indicating that governance metrics often scale with high-pressure contexts. The interaction term of industrial robotic penetration and environmental governance is positive, suggesting that governance attention increases where automation uptake is already responding to tougher environmental conditions. Robustness using Prais–Winsten confirms the signs and significance. Heterogeneity analysis reveals a stronger abatement effect of RBT in western regions—where scale effects are smaller and upgrading is earlier—and a weaker effect in the combined central–eastern group with dense industrial ecosystems. Policy implications are threefold: prioritise automation-led efficiency where marginal gains are largest; align governance with technology adoption and energy management rather than inputs alone; and differentiate regional pathways to synchronise industrial upgrading with decarbonisation.

Keywords: Industrial robotic penetration; Environmental Governance; Carbon emissions; Chinese Provinces.

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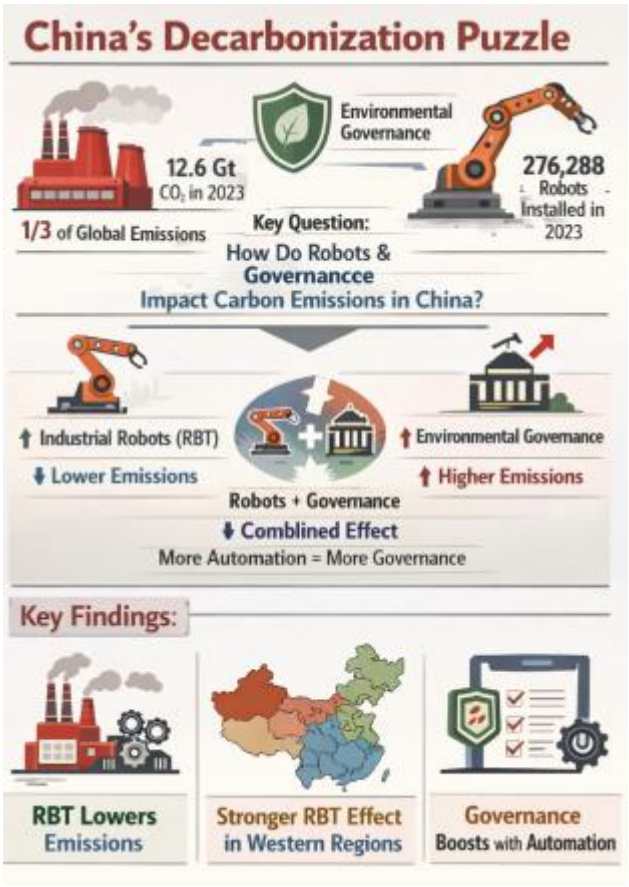
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Graphical abstract



1. Introduction

China is reported to produce 31.1% of the total worldwide energy-related CO2 emissions as of 2022, while this proportion increased again in 2023. On the other hand, China has also become the world's automation powerhouse: more than half of all new industrial robots installed in 2023 were deployed in China, and by late-2024 its robot density was estimated at about 470 units per 10,000 workers—now among the highest in the world (IFR, 2024). This pairing — very large emission with very deep robot penetration—creates a first-order policy question for provincial decision makers: does industrial robot adoption help, harm, or conditionally reshape the trajectory of carbon emissions across heterogeneous Chinese regions? The Ministry of Ecology and Environment published their initial documentation of the CNY 100 / tonne allowance price ceiling being broken on 24 April 2024 providing a definitive signal for the decarbonisation of industrial processes (MEE, 2024). At the same time Provincial Governments are still primary players in Environmental Governance, as they are responsible for implementing National Policy, and their own reports ("government work reports") also identify priority areas in Environmental Governance that influence Regulatory Enforcement and Corporate Behaviour. Liu *et al.* (2023) created a Province level database of "Environmental Attention" by systematically examining government work reports from 2003~2019, illustrating a correlation between higher levels of Governmental Attention to Environmental Issues and improved environmental performance.

J. Wang *et al.* (2023) utilised Urban Data collected from in Chinese Cities to demonstrate that the Adoption of Robots reduces Total Urban Carbon Dioxide emissions but generates a Rebound Effect by requiring Additional Energy Use that offsets some of the benefits; this Rebound Effect is greatest in Regions of China with a Reduced level of Industrialisation and the greatest level of Heterogeneity. In addition, at the firm level, Han and Zhang, (2024) found robots to have a significant impact on reducing pollution intensity, particularly when firms have strong internal controls and innovation capacity. In contrast, cross-country work by Zhang and Zhu (2023) shows that in certain contexts the effects of using "industrial intelligence" to reduce gross emissions can be countered by the dominant influence of scale effects. Taken collectively, all studies indicate that robots cannot be firmly categorised into either 'good' or 'bad' categories regarding their net impact on the climate; instead, we propose that the net impact is tabulated by factors such as governance quality, the energy mix used to produce, industry structure and stage of regional development.

With this backdrop in mind, this research paper will investigate how industrial robot penetration and environmental governance interact to affect

environmental quality (ecological footprint) within China over the time period (2007 to 2022), on a province-by-province basis. First, in place of using the more generic constructs of "digital economy" used in the previous studies mentioned above, we will use a more accurate, aggregate, and internationally comparable indicator of automation, provided by the International Federation of Robotics (IFR) robot stocks and installations; these are consistent in their definition of time series (i.e., they use the same methodology) and provide consistent variance of robot penetration across 31 provinces. Second, Liu *et al.* (2023) and Ren (2024), in recent advances in quantifying "governmental environmental attention," operationalise environmental governance utilising text-based indicators constructed from provincial government work reports. Third, to address the econometric problems that long provincial panels experience, we estimate a Feasible Generalised Least Squares (FGLS) model to accommodate the error structures of heteroskedasticity between provinces, serial correlation within provinces and cross-sectional dependence from national shocks, and test for robustness through the use of Prais-Winsten estimators with panel autocorrelation correction.

Hence, to investigate the differing interactions and coefficients of developed region(s) (hereafter referred to as "developed Regions") and developing region(s) ("Developing Regions"), we divided the sample based on the official three-way/east/west/north-east partition (NBS, 2025). The motivation for this is derived from the previous investigation by Yu *et al.* (2023) that found stronger impacts of robots on abatement in developed regions or less industrialised areas; furthermore, there is ample evidence that governance and enforcement capacities are very region-specific (Zhu *et al.*, 2023). The reminder of this paper is organised into the following sections: Section (2) discusses the literature, theory, and historical context of the relationship between carbon emissions and industrial robot penetration and environmental governance; Section (3) describes the methodology, data collection, and variable selection; Section (4) discusses the empirical findings and implications of this research; and Section (5) provides the conclusion and recommendations for policy changes.

2. Literature Review

2.1. *Industrial transformation, automation, and carbon emissions*

The rapid development of the industrial system in China has had significant implications for energy use and emissions. To date, no study appears to have directly estimated carbon emissions associated with automation; however, both sets of studies have identified ways through which automation could potentially reduce energy per unit of output through increased consistency, reduced scrap rates, and more streamlined processes, which are commonly referred to as "technique effects" in environmental economics. The identification of the connection between automation and energy consumption within the smart manufacturing literature supports the understanding of how data-driven manufacturing methodologies synchronise sensor networks, process control devices, and scheduling systems to minimise idle times and improve process stability to create initial energy savings (Kusiak, 2019b; Mittal *et al.*, 2020; Wang *et al.*, 2023). More broadly, the International Energy Agency's analysis has shown that the addition of digital technologies to process control and analysis capabilities can create an increase in energy productivity as well as potentially lead to increased energy consumption due to reduced costs and increased production levels as a result of increased efficiency and automation. The industrial context of China presents two key aspects that assist in understanding the general rules of the respective factors (e.g., the respective industrial emissions coming from heat-intensive sectors) involved. One such aspect is that, due to the thermal nature of these sectors, a large portion of the emissions generated within provinces in China come from the production of heat.

Recent studies of industrial decarbonisation in Chinese provinces have concluded that this relationship between control of processes and electrification of heat is a 'workhorse' of industrial decarbonisation effort; it should be noted, however, that such a relationship will be limited by regional electricity costs, and price and reliability of allowances will determine adoption at the plant level (LBNL, 2024; and Reuters, 2024). While the compositions of CO_2 emissions of production facilities will vary amongst provinces, the technical efficiency of plant processes will not change; thus, the technical efficiency gain of a facility will yield greater leverage to reduce CO_2 emissions in such provinces with less energy intensive activities, than will such facilities with energy intensive activities (Mi and Sun, 2021; and Wang and Feng, 2018). Research at both the firm and sector levels in China has determined that while the transition to digital and smart manufacturing reduces the energy intensity of production and increases green productivity when there is aggressive application of process control management systems, the largest effect is found in the Industries of Electronics, Machinery and Other Precision Dependent Industries (Chen *et al.*, 2024; Lin & Li, 2024).

Process optimisation is not a guarantee of improving energy efficiency as rate of output growth may exceed rate of productivity improvement if supply-chain demands are elastic and/or the energy supply source is dominated by coal energy usage. Therefore, industrial decarbonisation studies that cover China show the necessity of adopting both plant-level optimisation and electrification, in conjunction with decarbonisation of the energy supply, to translate potential into actual reductions in carbon emissions (Huang *et al.*, 2023; IEA, 2017; Ma *et al.*, 2023; Zhou *et al.*, 2019). The CEADS/Scientific Data inventories provide reliable and consistent information on provincial CO_2 emissions for 30 provinces starting from 1997 and the methodology has been updated since 2017; therefore, this data has formed the basis of the vast majority of recent literature regarding provincial emissions, productivity and peaking paths (Guo & Pang, 2023; Shan *et al.*, 2018; Shan

et al., 2020). Decomposition studies provide evidence that income, energy intensity and structure are the most significant drivers of cross-province differences, while forward-looking analyses of the peaking trajectories help to understand provincial variations in carbon-emission efficiency, and renewable energy supply (Guo & Pang, 2023; Li *et al.*, 2024; Wei & Wang, 2022; Wu & Gu, 2021). There are two cautions to mention in the literature when placing an emphasis on empirical methodology as well as subject matter: Firstly, because many provinces experience common national shocks and trade linkages, this requires careful consideration of cross-sectional dependence and persistence when specifying econometric designs (Chudik & Pesaran, 2015; Ditzen, 2018; M Hashem Pesaran, 2015).

The Environmental Kuznets Curve (EKC) has been shown to be inconclusive regarding the relationship between CO_2 emissions at the provincial levels in China across many pollutants and regions, although EKC-type curves associated with CO_2 emissions have been documented when industrial structure and technology are included in the models. The reviews and applications that have employed nighttime lights, spatial models, and quantile estimation indicate the presence of inverted-U curves with varying turning points based on development-stage and policy regime (Sarkodie & Strezov, 2019; Wang *et al.*, 2025; Wei, 2024; X. Zheng *et al.*, 2024). In relation to a governance/automation-centred understanding of the provincial model, it is critical to understand that omitting income from the models leads to the potential for misattributing the scale/composition dynamics and therefore erroneously attributing them to the technology. Therefore, the broad literature that exists outside the narrower" Robots → Carbon" niche area posits that it can be reasonably expected that automation will produce the greatest carbon reductions in environments where energy supplies are becoming cleaner and where high value is placed on process control and where provincial structures are moving up the value chain. In all other cases, rebounds will dilute carbon intensity gains (Wang *et al.*, 2024; Q. Wang *et al.*, 2023).

Numerous studies have examined the effects of industrial robotic penetration on carbon emissions in China. Using a provincial panel, Chen and Liu (2025) report that robot penetration reduces measured environmental pollution, with part of the effect operating through green innovation and skill-structure upgrading—two pathways consistent with the idea that programmable automation tightens process control and raises the payoff to cleaner techniques. The transmission logic of process stability and energy-saving innovation is shared with energy-related pollutants, although the net effect on CO_2 remains contingent on the provincial energy mix and industrial composition.

2.2. *Environmental governance and provincial carbon emissions*

Since the middle of the 2010s, Environmental Governance in China has progressed quickly with emissions impacts showing up in ambient data and firm behaviour. The Central Environmental Protection Inspections (CEPI) create a quasi-experimental opportunity to observe changes due to inspections: coal plants in cities where inspectors target have experienced decreases in SO_2 emissions for 1 month, between 25% and 52%, but the rebound patterns are heterogeneous depending on the ownership structures of the plants and the extent to which the inspectorate holds the facilities accountable after the inspections, highlighting that the presence/absence of credible oversight can change how companies run their operations "in real time" (Karplus *et al.*, 2018). The lesson learned about carbon is not directly translatable, however there is a clear understanding that the more extensively and predictably monitoring and penalties are made known to polluting facilities, the more they will adjust their output, abatement, or both; and the more Successful those adjustments will be at the provincial level when CEPI's are conducted broadly across provinces.

Two institutional reforms are often associated with improved environmental performance. One is the Environmental Vertical Management Reform (EVMR) implemented below the provincial level in 2016. Newly conducted empirical research has demonstrated that many of the firms subject to EVMR have significantly decreased their industrial water pollution and significantly increased their corporate environmental, social and governance (ESG) performance as a result of the redistribution of authority associated with the implementation of EVMR; this additional complementary research demonstrates the robustness of EVMR and, consequently, a reduction of the manipulation of environmental data by firms through increasing the credibility of the environmental data upon which the implementation of environmental policies rely (Tan *et al.*, 2024; Xu *et al.*, 2025; Yang Jing *et al.*, 2024; Zhou, 2020). Another new governance model that was also implemented to increase cross-jurisdictional accountability for water quality is called the River Chief System (RCS). Ecosystem assessments identify patterns of decreased chemical oxygen demand (COD) and ammonia nitrogen (NH3-N) within counties that share borders and as well show general improvements in coordinated watershed management (coordinated watershed management is a system that allows multiple stakeholder organizations to work together to improve watershed) However, these assessments were predominantly focused on advancing information about better water management systems; in a manner that has parallels to air and also carbon dioxide (CO2) where numerous entities will experience the flow over time. (Huang, *et al.*, 2024; Mu, *et al.*, 2025; Shen, *et al.*, 2024). Examples of the second-tier evidence involving market-based instruments and increased transparency are the most compelling examples of successful application of this theory. China's national emissions trading scheme (ETS) has been operational since 2021 and has already become the largest ETS in the world by emissions covered. With the issuance of allowances in 2023, this system has begun to direct generating patterns of electricity and encourage investment to help regulate compliance. While continuing to evolve; it is clear from early analysis/reports, that the choice of benchmark level and allowance pricing path are critical factors for the scale of emissions abatement, and there are indications from plant-level assessments that

there have been both production reductions and decreases in observed emissions. (Fischer *et al.*, 2024; ICAP, 2024; Wang *et al.*, 2025).

Environmental information disclosure (EID) continues to grow through the use of mandatory environmental reporting combined with civil-society data platforms (EID), including the Blue Map from the Institute of Public & Environmental Affairs (IPE). There is a body of evidence linking EID with improved corporate environmental performance, higher levels of green total factor productivity (TFP), and improved carbon-efficiency metrics through several different mechanisms including access to financing; pressure from reputational concerns; and being able to screen the supply chain (Gu and Qiao, 2024; Hu, *et al.*, 2025; IPE, 2021/2024; Lan *et al.*, 2025; Ye *et al.*, 2023). Political economy has an important role in carbon emission reduction and can be used as an influence on a firm's decision-making. Cadre evaluation studies show how promotion leads to the same environmental results as growth targets and affect a firm's enforcement intensity (Liu *et al.*, 2021; Yang *et al.*, 2024). There are also four reoccurring findings in synthesising China's climate governance; central steering, experimental localism, information disclosure, and policy integration (Li & Gallagher, 2022). In many instances where there are high emissions, fiscal decentralisation and administrative decentralisation do not align with the carbon emission reduction objectives, resulting in dilution (Liu & Yang, 2022). Additionally, the way provinces govern and the types of energy and energy endowments they have can affect how much emissions are reduced. The spatial studies that have been done indicate that where there are upgrades to the industrial structure and energy endowments favour a lower carbon production system, the same policy will lead to better results. When there are areas with heavy industry and power generation relying on coal, the policy will require more effort to reduce emissions (Li *et al.*, 2024; Wu & Gu, 2021; Zheng *et al.*, 2024).

Recent shifts in China's policy landscape also show that environmental governance can be measured and that credible oversight reshapes plant-level behaviour in real time. The Central Environmental Protection Inspections demonstrate that credible oversight can prompt the real-time re-optimisation of plant operations (Karplus & Zhang, 2023), while the national Emissions Trading System (ETS)—the largest in the world by covered emissions—provides a carbon price signal that raises the salience of compliance investment and is expected to further discipline the trajectory of provincial emissions as its coverage expands (ICAP, 2024).

2.3. *Summary and research gap*

The broader literature related to modelling provincial emissions from all sources of CO_2 in China produces three important implications for this research. First, in the area of measurement, third-party data on large scale automated robots provide an independent and transparent metric by which to assess the use of automation across provinces. In addition, the energy use by provinces was tracked through CEADS/Scientific Data data, which is a valuable source of reliable information to assist in uniform assessment and analysis of energy inventory and CO_2 emissions for the entire country (ICAP, 2024; Karplus and Wu, 2023; Shan *et al.* 2018; Shan *et al.*, 2020; Xu *et al.*, 2025). Second, in terms of heterogeneity of industrial structure and energy endowment, provinces vary significantly from one another in terms of their relative degree of carbon use and energy consumption. Studies on carbon intensity, energy intensity and their relationships with emissions and energy consumption have produced different findings for industrial structures and energy endowments, thereby creating significant variability in how technology and governance translate to carbon abatement in the various provinces (Guo *et al.*, 2024; Liu *et al.*, 2025; Wu & Gu, 2021). Third, econometrics: provincial panels share national shocks and exhibit serial persistence; designs should therefore allow for cross-sectional dependence and dynamics (e.g., common-correlated effects or robust covariance structures) and retain income and income-squared terms to avoid conflating EKC-type curvature with technology or policy effects (Chudik & Pesaran, 2015; Ditzen, 2018; Wang *et al.*, 2024).

3. Model, methodology, and data

3.1. *Theoretical relationship and statistical model*

This study treats provincial carbon emissions as the outcome of two elements, policy-salient forces that operate inside production and regulation: the penetration of industrial automation and the quality of environmental governance. Initially, we modeled them as separate drivers of emissions because the underlying channels differ in both economics and implementation. Second, we use the interaction term of to analyse the potential effects of both elements to influence carbon emissions. **Figure 1** illustrates the overall empirical strategy followed in this study.

On the production side, industrial automation reshapes the transformation of inputs into output. Studies of robot diffusion across advanced economies show that automation raises productivity by stabilising processes, lowering defect rates, and smoothing throughput—mechanisms that typically compress energy use per unit of output (a classic "technique effect"). Robotic technology contributed to productivity increase in 17 countries via better process control and lower amount of wasted energy required to fix mistakes on production lines, it was found by Graetz and Michaels (2018). Acemoglu and Restrepo (2020) argue that automatizing tasks creates a shift in the workplace tasks into places where they are completed at a lower factor price, thus allowing greater amounts of energy to be consumed at a lower rate; hence, although energy intensity is reduced, the overall impact on pollution will vary based on a particular country's economic situation and context. The International Energy Agency (IEA) has also conducted synthesis of digitalisation in the energy sector. This analysis supports the theory that increased use of digital control and analytics increases the efficiency of energy use; however, if businesses lower their costs and continue to operate as previously, they may create an increase in energy use, which may result in a rebound effect. These observations motivate an elasticity of emissions with respect to automation that is expected to

be negative when technique and composition effects dominate scale, and smaller (or even neutral) where demand is elastic or the power mix remains carbon-intensive (IEA, 2017).

Building on this evidence, this study expects the elasticity of emissions with respect to automation to be weakly negative on average, while recognising that provincial heterogeneity in energy mix and industrial structure can attenuate the effect (Liu, 2023). On the regulatory side, governance arrangements that bundle monitoring intensity, credible enforcement, information disclosure, and market instruments raise the expected cost of carbon-intensive operations. On theoretical grounds, therefore, an inverse relationship is expected between emissions and governance intensity, irrespective of the technology employed (Karplus & Wu, 2023).

Theoretically, our model includes three well-established mechanisms:(1) The income-growth–scale–composition–method decomposition underlying the Environmental Kuznets Curve (EKC). For example, in empirical studies conducted in a regional context of China, researchers have documented the presence of EKC-type non-linearities, including inverted U-shape relationships for CO2 emissions when accounting for regional policies or industrial structure (Azimi and Bian, 2023; Li *et al.*, 2024); (2) the automation-decarbonisation channel whereby robots lead to a reduction in manufacturing defects, the optimisation of thermodynamic cycles, the stabilisation of production throughput, and provide for more accurate dosing of raw materials to increase energy productivity, therefore reducing manufacturing process emissions (Han and Zhang, 2024; Xie *et al.*, 2023); and (3) the rebound effect, as outlined by Wang *et al.* (2023). Consequently, including both linear and squared GDP terms is necessary to test for the presence of both EKC and automation-governance mechanisms in the broader provincial panel context. CD test routinely rejects independence in Chinese provincial panels, while Wooldridge's test frequently flags AR(1) serial correlation; both features, if ignored, bias standard errors and can distort inference (Pesaran *et al.*, 2004; Wooldridge, 2003). We also acknowledge the famous advice by Beck and Katz (1995) that some forms of GLS can produce over-confident standard errors under misspecification, which is why we report Prais and Winsten (1954) estimates as a robustness check and use panel-appropriate tests prior to estimation.

Lastly, we do allow for non-linear income effects for Environmental Kuznets-like dynamics within subnational China. Many recent studies, using prefectural or provincial data, have discovered inverted-U (inverted U-shaped) relationships for CO_2 once structure and technology are included in the model, which warns against attributing the curvature of growth to automation or governance (Y. Zheng *et al.*, 2024). In our setting, this is handled parsimoniously by entering GDP per capita and its square. Bringing these elements together, the baseline statistical model for province i in year t is proposed in linear form as:

$$CO2_{it} = \alpha_i + \beta_1 RBT_{it} + \beta_2 ENV_Gov_{it} + \beta_3 GDP_{it} + \beta_4 Energy_{it} + \beta_5 Labor_{it} + \beta_6 IND_{it} + \varepsilon_{it} \quad (1)$$

where $CO2_{it}$ is the carbon emissions in province *i* in year *t*, *RBT* is the industrial robotic penetration in each province, *Env_Gov* is the environmental governance framework stringency, *GPD* is gross domestic product, Energy is the Energy consumption in each province, *Labor* represents the number of people employed in each province, and *IND* represents the industrialisation in each province. This is the non-linear form to test the EKC hypothesis:

$$CO2_{it} = \alpha_i + \beta_1 RBT_{it} + \beta_2 ENV_Gov_{it} + \beta_3 GDP_{it} + \beta_4 GDP2_{it} + \beta_5 Energy_{it} + \beta_6 Labor_{it} + \beta_7 IND_{it} + \varepsilon_{it} \quad (2)$$

where GDP2 is the double of the economic output, and to verify that either when GDP is doubled, whether carbon emissions are negatively or positively affected.

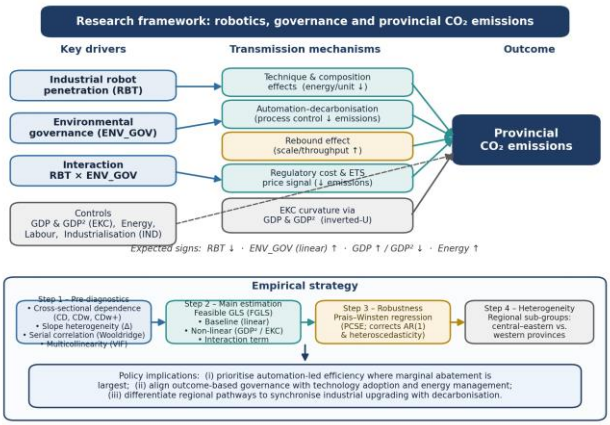


Figure 1. Research framework linking industrial robot penetration, environmental governance and provincial CO_2 emissions, with the empirical estimation strategy.

3.2. *Econometric modelling*

In recent research, a variety of statistical methods have been applied to panel data, but before jumping into any model, it's essential to first understand the nature of the dataset. Skipping this step can lead to biased or unreliable results. Panel data often presents specific statistical issues such as cross-sectional dependence (CSD), serial correlation, heteroscedasticity, and slope heterogeneity. Early identification and resolution of features that threaten the reliability of the econometric process are necessary for the implementation of economically sound and effective econometric practice. Once you have identified the issues, you can apply these alternative methods: FGLS (Hansen, 2007), which is frequently superior to ordinary least squares (OLS) in terms of consistency and reliability depending upon heteroscedasticity and cross-sectional dependence (Bai *et al.*, 2021); and the Prais-Winsten method, which is readily available (Beck and Katz, 1995), but is recommended when conducting unbiased panel data estimates. This study employs multiple methods to test for cross-sectional dependence, including well-known techniques: the Pesaran CD test (Pesaran, 2015; Pesaran and Xie, 2021), Juodis and Reese's CDw (2021), and Fan *et al.*'s CDw+ (2015). The CD test is generally the most widely used technique and produces a statistic by determining the average pairwise correlation and squared correlations of the estimated residuals between all units. Juodis and Reese augment this with the CDw by including a weighting matrix that allows for differences in the strength of the cross-

sectional relationships. The CDw+ test enhances the sensitivity of the CDw to detect less robust forms of dependence. These equations (3) to (5) present the equations for all these CD tests:

$$CD = \frac{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}\hat{\rho}_{ij}}{\frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1}^{N}\hat{\rho}_{ij}} \quad (3)$$

$$CD_{w} = \frac{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}w_{ij}\cdot\hat{\rho}_{ij}}{\frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1}^{N}w_{ij}\cdot\hat{\rho}_{ij}} \quad (4)$$

$$CD_{w+} = \left(\frac{\frac{1}{N}\sum_{i=1}^{N}\sum_{j=1}^{N}w_{ij}\cdot\hat{\rho}_{ij}}{\frac{1}{N(N+1)}\sum_{i=1}^{N}\sum_{j=1}^{N}w_{ij}\cdot\hat{\rho}_{ij}}\right)^{\alpha} \quad (5)$$

In equations (3 - 5), *N* denotes the number of cross-sections, $\hat{\rho}_{ij}$ represents the residual correlations between cross-sections *i* and *j,* w_{ij} indicates the weight matrix in CD_w, and α is the power enhancement parameter in CD_{w+} test. Bersvendsen and Ditzen (2021) outline three distinct specifications for examining slope heterogeneity in panel data models: the standard test, a heteroscedasticity and autocorrelation consistent (HAC) robust test, and a cross-sectional dependence (CSD) robust test. The standard test operates under the assumption of homoscedastic error variance; however, when this assumption is violated, the HAC robust variant offers greater reliability by relaxing the constraints related to both homoscedasticity and autocorrelation. In contrast, the CSD robust specification explicitly accounts for cross-sectional dependence, thereby producing more reliable estimates in the presence of such dependence structures. In these procedures, the null hypothesis asserts that slope coefficients are homogeneous across cross-sectional units. Rejection of the null—typically at a 5% significance threshold—indicates the presence of slope heterogeneity. The mathematical formulations for these slope heterogeneity tests are summarised in the following equations:

$$\hat{H} = \frac{1}{\sqrt{N}}\left(\frac{\sum_{i=1}^{N}\tilde{\Delta}_i - k_2}{\sqrt{2k_2}}\right) \quad (6)$$

$$\hat{H}_{HAC} = \sqrt{N}\left(\frac{S_{HAC} - k_2}{N\sqrt{2k_2}}\right) \quad (7)$$

$$\hat{H}_{CSD} = \mu_i + \dot{\beta}_{1i}^{'}X_{1i,t} + \dot{\beta}_{2i}^{'}X_{2i,t} + \sum_{l=1}^{PCSA}\gamma_{i,t}\varpi_t + \varepsilon_{i,t} \quad (8)$$

In above equations, $\tilde{\Delta}_i = \left(\hat{\beta}_{2i} - \tilde{\beta}_{2WFE}\right)\frac{\dot{X}_{2i}^{'}I_i X_{2i}}{\tilde{\sigma}_i^2}\left(\hat{\beta}_{2i} - \tilde{\beta}_{2WFE}\right)$, k will be considered as the unknown slope coefficient, I_{1i} represent the identity matrix, $\hat{\beta}$ and $\tilde{\beta}_{2WFE}$ in the above equations are the slop coefficients, which will be estimated under the methods of pooled OLS and weighted effect method respectively, S is the Swamy's test statistic, $S_{HAC} = \Sigma T_i\left(\hat{\beta}_{2i} - \hat{\beta}_{2HAC}\right)^{'}\hat{Q}_{i,T_i}\hat{\varpi}_{i,T_i}^{-1}\quad \hat{Q}_{i,T_i}\left(\hat{\beta}_{2i} - \hat{\beta}_{2HAC}\right)$, $\bar{\omega}_t$ denotes cross-sectional averages, and $\varpi_t = N^{-1}\sum_{j=1}^{N}\left(X_{1j,t}, X_{2j,t}, Y_{j,t}\right)$.

In **Table 4**, the parameters reported under "Delta" and "Adjusted delta" are the Pesaran–Yamagata (2008) standardised dispersion statistics used to test the null hypothesis of slope homogeneity. "Delta" denotes the standardised statistic $\Delta = \sqrt{N}\cdot(N^{-1}S - k)/\sqrt{(2k)}$, where N is the number of provinces, k is the number of slope parameters being tested, and S is Swamy's statistic measuring the weighted dispersion of the province-specific slope estimates around the pooled weighted estimate. "Adjusted delta" is the bias-adjusted version, which applies a small-sample mean–variance correction and is preferred when the time dimension of the panel is finite. Under the null of homogeneous slopes both statistics are asymptotically standard normal; larger and statistically significant values therefore indicate stronger evidence that the response of carbon emissions to the regressors varies across provinces, which motivates the use of estimators that accommodate slope heterogeneity.

To assess multicollinearity among explanatory variables, the variance inflation factor (VIF) serves as the diagnostic tool, and this multicollinearity can pose challenges because of the data deficiency. Typically, a VIF less than 10, derived from $VIF = \left(1 - R_j^2\right)^{-1}$ is preferred because it suggests that X_{ij} don't have any correlation, and it aids to interpret regression results. Finally, the Wooldridge test is employed to detect first-order autocorrelation in panel datasets. As an extension of the Breusch–Godfrey (BG) Lagrange Multiplier (LM) test, the Wooldridge procedure accounts for both cross-sectional and time-series dependence. In the BG–LM framework, the LM statistic is calculated using t to represent the number of time periods, while R^2 is obtained by regressing the first-differenced residuals on their lagged values. This refinement enhances the ability to identify serial correlation, thereby contributing to more reliable panel data analysis.

This research will evaluate the influence of the impact of Robotic Technology on Carbon Emissions using an examination of the Interaction of a Panel Data set of 30 Provinces within China through an Application of Feasible Generalised Least Squares estimation when Cross Sectional Dependencies (CSD) Serial Correlation and Heteroscedasticity and/or Heterogeneity on the slope are present within the panel data set. FGLS demonstrates stronger in-sample forecasting performance than ordinary

least squares (OLS) and effectively addresses issues of heteroscedasticity, autocorrelation, and cross-sectional dependence (Bai *et al.*, 2021). In addition, Prais–Winsten regression (Beck & Katz, 1995) is implemented as a robustness check, given its suitability for short panels and its ability to correct for heteroscedasticity and autocorrelation. Both FGLS and Prais–Winsten have been chosen for their robustness in handling the typical statistical complexities of panel data, with FGLS is more advantages over alternatives such as GMM when cross-sectional dependence is found among the cross-sectional units.

3.3. *Data and Variables of study*

3.3.1. Data

This study uses panel data for 30 Chinese provinces over the period 2007~2022. Mainland China comprises 31 provincial-level administrative divisions—22 provinces, 5 autonomous regions, and 4 directly administered municipalities—excluding the Hong Kong and Macao Special Administrative Regions and Taiwan. Of these, the present study covers 30 provincial-level units; Tibet (Xizang) is excluded because consistent province-level data on industrial robot installations and several of the control variables are not reported throughout the full sample period in the statistical sources used. The main data sources are the databases of "International Federation of Robotics", provincial "Government Work Reports", "China Statistical Yearbook", "China Environmental Yearbook", "China Energy Statistical Yearbook", and "China Stock Market & Accounting Research Database" (CSMAR). To address missing values for some years, this study applies linear interpolation, a regression-based imputation approach, and the five-year moving average; the potential influence of these imputed observations on the estimates is acknowledged as a limitation in the concluding section. The final sample comprises 480 observations.

3.3.2. Variables of study

3.3.2.1 SectoCarbon emissions (CO2): Dependent variable

This study uses province–year carbon emissions and take the natural logarithm of total CO_2 from fossil-fuel combustion and other processes as our baseline measure, following inventory practice in the IPCC guidelines. For robustness, we construct a per-capita version by dividing provincial totals by resident population and again apply the log transform (Shan *et al.*, 2020; Zhang & Lin, 2012).

3.3.2.3 Industrial robot penetration: Independent variable

We measure provincial robotic penetration using annual installation figures from the International Federation of Robotics (IFR, 2024). We build the standard intensity measure for each province and year by dividing the total number of robots reported by International Federation of Robotics (IFR) in that province and year by the number of employees employed in the manufacturing sector within that province according to the Statistical Yearbooks of China. The few small gaps in the data have been filled using a consistent interpolation process and aligning the reporting of IFR with the provincial boundaries in the Statistical Yearbooks of China.

3.3.2.4 Environmental Governance: Independent variable

This study measured the provincial level of environmental governance using a compact, dictionary-style textual analysis of provincial Government Work Reports (GWRs). Following established methods in the Chinese policy-text literature (Shiyi & Dengke, 2022; Yang *et al.*, 2023; Zhao *et al.*, 2021), each report was segmented in Python and the frequency of a curated set of environment- and regulation-related terms (e.g., emissions, pollution control, low-carbon transition, ecological protection) was counted. Term counts were normalised by the length of each report and then aggregated by province to construct a provincial environmental governance score, which was subsequently z-standardised relative to all government work reports in each year. The resulting index captures the relative importance that provincial governments attach to environmental governance in their published reports.

3.3.2.5 Control variables

The five control variables used in this study include gross domestic product (GDP measured as log of GDP/capita in the regions, regional energy consumption measured as log of the total energy consumed within each province, industrialisation (IND) measured as total industrial output per province and regional GDP, and labour (L) measured as log(n) of the number of employed people in the provinces).

4. Empirical analysis and findings

4.1. *Descriptive analysis*

Table 1 summarises the patterns for the province-year data (30 provinces) and trend data in China (2007~2022), highlighting the close alignment of means and medians across all datasets; however, regarding the two primary predictors, Robotics (mean 6.136/median 6.095) and Environment governance (mean 3.948/median 3.970), they are also very similar. Robotics (the degree to which a province has adopted industrial Robots) has the widest variability of the three key variables (3.152–10.402; standard deviation 1.328), indicating the uneven distribution of Automation among provinces. While RBT has a modest right-skew of 0.143 and a relatively mesokurtic (kurtosis 2.335), indicating moderate variation in RBT without extreme outliers. Conversely, the environmental governance variable (ENV_GOV) has a tighter range (standard deviation 0.384) and displays significant left skewness (-0.923) and high tail weight (kurtosis 6.158), indicating that some of the provinces have very high governance ratings, while others have extremely low governance ratings, which provide some interesting variation when examining how governance influences emissions. CO2 emissions are generally evenly distributed across provinces (standard deviation 0.348; highest-lowest 3.455–5.181). There are wide-ranging values for the Energy and IND variables, driven by a small number of province–year observations recorded as zero in the source yearbooks. These zero-coded values—for example, IND in 2018 and Energy and Labor in isolated years—were retained after imputation and are responsible for the abrupt dips visible in the corresponding panels of **Figure 2** and for the heavy left tails (high kurtosis) noted above; they do not reflect genuine year-on-year collapses in industrial output or

energy use. The Labor emissions variable has a significant left tail. Importantly, all standard deviations for the various variables are comfortably below 3 and indicate that there is not excessive volatility in the province-year data. Although the dataset is fairly large (480 observations), with some minor deviations from Normal, the statistical significance of the Jarque-Bera tests indicates that robotics and environmental governance are not normally distributed because of skewness and tail thickness. The data show a high degree of heterogeneity across provinces for both Robotics and Environmental Governance and therefore provide the necessary variation to test how robotics and environmental governance shape CO2 emissions, while the controls capture variation in energy consumption, economic scale, employment, and industry.

Table 1. Descriptive statistics.

Variables:	CO2	RBT	ENV_GOV	Energy	GDP	Labor	IND
Mean	4.424	6.136	3.948	4.022	4.649	2.508	3.515
Median	4.432	6.095	3.970	4.065	4.666	2.633	3.758
Maximum	5.181	10.402	4.828	4.683	5.279	3.324	4.687
Minimum	3.455	3.152	1.946	0.000	3.840	−0.146	0.000
Std. Dev.	0.348	1.328	0.384	0.541	0.255	0.556	1.005
Skewness	−0.261	0.143	−0.923	−5.179	−0.222	−2.100	−2.586
Kurtosis	2.688	2.335	6.158	38.749	2.902	8.231	9.509
Jarque–Bera	7.406	10.483	267.582	706.095	4.126	900.020	1,382.19
Probability	0.025	0.005	0.000	0.000	0.012	0.000	0.000
Observations	480	480	480	480	480	480	480

Table 2. Pairwise correlation matrix.

Variables	CO2	RBT	ENV_GOV	Energy	GDP	Labor	IND
CO2	1						
RBT	−0.157***	1					
ENV_GOV	−0.083*	0.361***	1				
Energy	0.513***	−0.031	−0.009	1			
GDP	0.045	0.610***	0.254***	0.073	1		
Labor	0.353***	0.207***	0.122***	0.244***	0.329***	1	
IND	0.188***	−0.041	−0.160***	0.129***	0.087*	0.175***	1

*Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%.*

From the correlation matrix (**Table 2**), it can be said that industrial robotic penetration leads to lower CO2 emissions. The negative association between RBT and CO2 (-0.157) suggests that provinces whose companies have higher levels of automation may emit fewer carbon pollutants. The next most significant negative relationship is between environmental governance (ENV_GOV) and CO2 (-0.083) indicating that provinces with more effective environmental regulatory systems produce less CO2 than those with less effective systems. In contrast, energy use has the most significant correlation with CO2 production (0.513), indicating that energy consumption plays an important role in CO2 production. The positive correlations between labour (0.353) and industrialisation (0.188) with CO2 indicate that these two factors also contribute to CO2 production, but to a much lesser extent than energy consumption. The relationship between economic output (GDP) and CO2 emissions is negligible (0.045). In the explanatory block, RBT is highly correlated with GDP (0.610) and moderately correlated with ENV_GOV (0.361), suggesting that provinces with higher levels of productivity and better environmental governance are more likely to cluster. ENV_GOV and GDP are positively correlated (0.254), and ENV_GOV and labour are also positively correlated (0.122), however, the negative association between ENV_GOV and industrialisation (-0.160) indicates that provinces with greater levels of industrialisation tend to have lower levels of environmental governance capacity. Energy is weakly correlated with most of the other factors, but it is positively related to both labour and industrialisation (IND). Overall, most pairwise relationships between CO2 and the other variables are weak to moderate, however, there is a strong dependence on RBT and GDP and this should be included in diagnostic multicollinearity testing. Moreover, **Figures 3 and 4** illustrate the nexus of explained variables with the explanatory variable.

4.2. *Inferential analysis*

4.2.1. Pre-diagnostics

The provincial panel data exhibit a cross-sectional dependence—this has been clearly and consistently supported through the use of diagnostics for the panel data presented in this study. For the different time series assessed, such as CO2, Labor, and IND, all three types of cross-sectional dependence tests conducted in this study (Pesaran CD test, Pesaran weighted CDw test, Pesaran power CDw^{+} test) showed high levels of significant correlation (1% level), suggesting that the provinces are correlated in their movements in response to shocks incurred by the provinces, spillover policies, supply chain interconnections, and energy supply and technology cycles. Furthermore, both of the focal predictors of this study (RBT and ENV_GOV) display significant cross-sectional correlation—both are indicative of national diffusion of automation technology and provincial governance

benchmarking. As the results from these analyses suggest, these results provide a reason for making use of regression models and regression standard errors that can account for cross-sectional dependence when estimating the parameters of the regressions. The VIF analysis also supports this conclusion, as all of the VIFs calculated for all of the independent variables were within acceptable ranges (ranging from approximately 1.08 to 1.74), with the highest VIFs being observed for RBT and GDP. The results from the VIF analysis indicate that there is minimal linear dependence between the independent variables and thus the precision of the coefficient estimates will not be compromised as a result of multicollinearity. Thus the data from this study show a great deal of cross-sectional dependence but also indicate that the predictors are quite distinct from one another, which provides a context for using models that will be capable of explicitly taking into account the geographic interdependence of the provinces in the future.

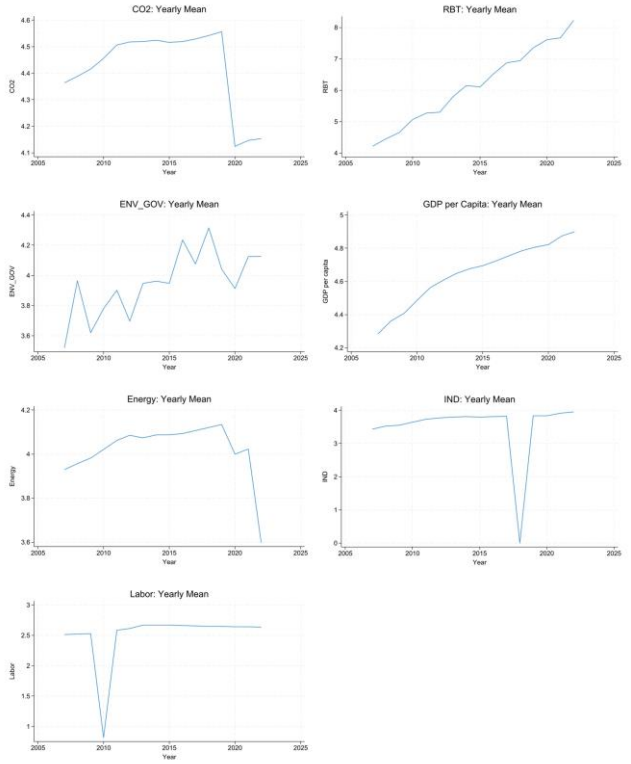


Figure 2. Mean trend of the variables over the sample period (2007–2022).

4.2.2. Heteroscedasticity, Homogeneity, and autocorrelation

Table 4 demonstrates definitively that the response coefficient does vary among the units (provinces) of observation in this study. The Pesaran-Yamagata test and the adjusted version of this test reject the null hypothesis of slope homogeneity at the 0.01 level of significance, and the HAC-robust Blomquist-Westerlund statistics reject the null hypothesis at conventional significance levels, indicating there is a heterogeneous slope in this case. When cross-sectional dependence is taken into account (by including cross-sectional averages) in testing for veracity of estimated coefficients, the rejection is stronger; therefore, we cannot conclude that all units (provinces) have a common elasticity (sensitivity) of CO2 output when compared to robotics, environmental governance and the other control variables in our study. The dynamics in this study are supported by the acceptance of the Wooldridge test findings that produced an F-statistic greater than one thousand and the sample size indicates that there is first order serial correlation within units (provinces) producing emissions. Thus, we conclude that shocks produced from emissions will exhibit persistence over time and thus require use of auto-correlation-robust procedures in the model specification. In comparison to the LR test, there is no evidence that indicates the existence of a heteroscedasticity problem, therefore, we conclude that errors across provinces have similar error variance. Lastly, the summary of these diagnostics provides sufficient support for us to utilise estimators and inference that allows for updated slope coefficients (i.e., heterogeneous slope coefficients), serial correlation, and cross-sectional connections in estimates as compared to standard estimation and inference techniques that do not allow for these important diagnostic factors. Consequently, we conclude that Feasible Generalised Least Squares (FGLS) or cluster- and Prais-Winsten regression modelling is most appropriate for reliable estimates of the influence of robotics and environmental governance in the overall carbon emission production process.

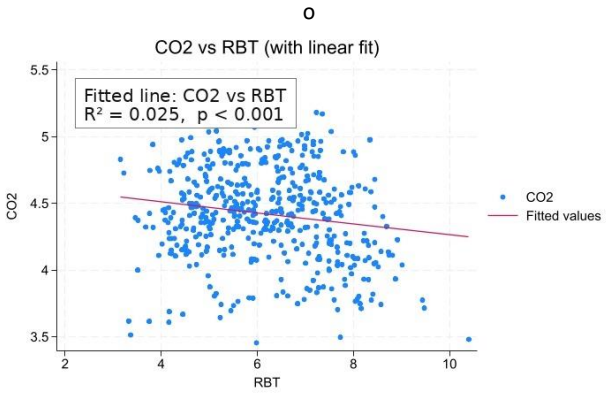


Figure 3. The nexus between RBT and CO2 across provincial units.

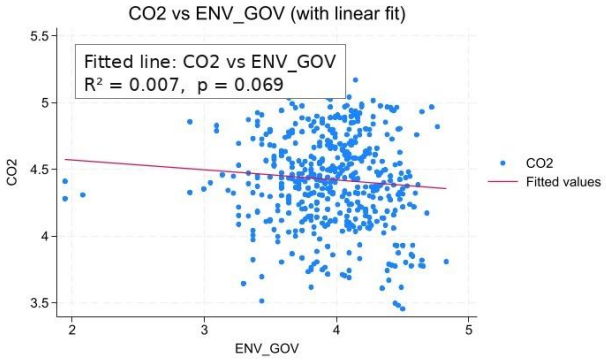


Figure 3. The nexus between ENV_GOV and CO2 across provincial units.

Table 3. CSD and multicollinearity test.

Variables	CD test	CDw test	CDw+ test	VIF
CO2	72.37***	5.79***	1515.66***	–
	(0.000)	(0.000)	(0.000)	
RBT	70.96***	5.41***	1485.39***	1.74
	(0.000)	(0.000)	(0.000)	
ENV_GOV	30.00***	2.79***	634.71***	1.19
	(0.000)	(0.005)	(0.000)	
Energy	46.39***	4.31***	1217.02***	1.08
	(0.000)	(0.000)	(0.000)	
GDP	80.33***	6.66***	1682.13***	1.73
	(0.000)	(0.000)	(0.000)	
Labor	82.23***	6.41***	1721.47***	1.21
	(0.000)	(0.000)	(0.000)	
IND	82.87***	6.64***	1735.13***	1.09
	(0.000)	(0.000)	(0.000)	

Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%.

Table 4. Heteroscedasticity, Homogeneity, and autocorrelation.

Heterogeneity test type	Delta	Adjusted delta
Standard test (Pesaran–Yamagata, 2008)	2.263**	3.200***
	(0.024)	(0.001)
HAC robust test (Blomquist–Westerlund, 2013)	0.760**	1.075**
	(0.044)	(0.028)
CSD robust test (with cross-sectional averages)	−9.487***	−6.481***
	(0.000)	(0.000)
Wooldridge test (Autocorrelation)	F = 1095.428***	Prob > F = 0.0000
LR test (Heteroscedasticity)	LR chi2 = 000	Prob.>chi2 =1.000

*Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%. P-values are presented in brackets.*

4.3. *Feasible GLS results*

Table 5 reports the first regression results of the parameter estimates for the FGLS model. When looking at these results from an FGLS perspective, it is apparent that provinces that have increased their use of industrial robots have been successful in reducing overall emissions, as shown by the negative coefficient of RBT (-0.026). The greater the degree of robotic deployment in the province, the lower the level of carbon dioxide (CO_2) emissions, controlling for all other variables. These results corroborate those from recent studies that state robotics promote higher levels of energy productivity and facilitate more green processing practices, thus resulting in actual measurable reductions of pollution in various Chinese provinces and industries (Liu, 2023; Yao *et al.*, 2024). In contrast, the Environmental Governance Index has a positive coefficient (0.018). This result can be interpreted as indicating that when high scores are assigned to a province on the Environmental Governance Index, this indicates that there is more effort and communication from the government and regulatory agencies in dealing with environmental issues that are occurring within that province compared to lesser scores on the Environmental Governance Index. In addition to this, there is a large variance between provinces concerning how many resources are allocated to developing governance and organizational structures; this is usually the case for places that have the largest amount of pressure from environmental issues (Liu *et al.* 2023; Jianxun Yang *et al.*, 2024). The control variables demonstrate that energy and GDP have a direct relationship with the increase in emissions due to their use of energy and economic scale (Energy = 0.079; GDP = 0.117), while labour and industry only have an indirect relationship with the increase in CO_2 emissions (Labor = 0.005; IND = 0.007). Overall, results from Column (1) provide evidence that robotic technology will help mitigate emissions due to their potential to facilitate the creation of more efficient processes and improve energy productivity when used in conjunction with governance indicators that are associated with mobilising effort or resources to address the issues associated with CO_2 emissions in higher-emitting provinces.

Additionally, checking for a possible nonlinear relationship between GDP and CO_2 has shown an inverted U-shape; i.e., GDP increased initially resulted in an increase in CO_2, but then after reaching a peak, GDP continued to decline for every subsequent dollar increase in GDP.The linear GDP variable is 4.511, while the square term is −0.479, suggesting that the findings suggest a transition between increasing and reducing emissions within the range of observed provincial income; emissions started to increase during the earlier part of development before declining as cleaner technologies and stronger government regulations became more widely available. The findings support the Environmental Kuznets Curve literature regarding China and other global studies documenting income-dependent

changes in pollution (Li *et al.*, 2016; Stern, 2004). Furthermore, when EKC is accounted for, the robot channel continues to reduce emissions as shown by the negative coefficient of the interaction between RBT and ENV_GOV (-0.029), as well as by previous studies demonstrating that these automation upgrades improve equipment efficiency, promote green innovation and assist provinces as they transition down the right side of the curve (Yao *et al.*, 2024). The governance variable remained positive (0.019) again confirming the previous findings where governance measurements capture efforts to address environmental issues, and usually portray policy efforts where there are (or have been) significant environmental issues, with further supporting studies indicating that through longer periods of time, governance quality and coordination generally dictate how rapidly provinces will be able to convert the efforts they have made into actual reductions in emissions (Jianxun Yang *et al.*, 2024).

Table 5. Feasible GLS estimates.

Variables	Baseline	Non-Linear	Interaction term
	Column (1)	Column (2)	Column (3)
RBT	−0.026***	−0.029***	−0.050***
	(−13.32)	(−22.22)	(−4.89)
ENV_GOV	0.018***	0.019***	−0.014
	(4.39)	(5.17)	(−0.83)
RBT × ENV_GOV	—	—	0.005**
			(1.99)
Energy	0.079***	0.077***	0.088***
	(11.17)	(21.44)	(17.46)
GDP	0.117***	4.511***	0.135***
	(10.18)	(19.44)	(11.83)
GDP^2	—	−0.479***	—
		(−18.59)	
Labor	0.005	0.019***	0.011***
	(1.28)	(7.26)	(3.43)
IND	0.007***	0.006***	0.000
	(2.98)	(3.66)	(0.14)
Constant	3.624***	−6.420***	3.644***
	(58.58)	(−12.22)	(41.55)
Wald χ^2	338.25	1404.38	773.61
Prob > χ^2	0.000	0.000	0.000
Observations	480	480	480

*Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%. T-values are presented in brackets.*

Adding the interaction between robot and governance measurement resulted in an ameliorating effect. The direct RBT variable was a greater negative (-0.050), which indicates a stronger average relationship between decreases in emissions from automation; while the interaction variable RBT × ENV_GOV was positive (0.005). Effectively, this demonstrates that in areas of fast-growing industrial centres where automation is enhancing efficiency, it is likely that the efficiency gains from robots are at least partially offset by the investment in scaling or compliance requirements at lower system levels. Energy efficiency rebounds and production growth in regulated innovation-active areas are well-documented mechanisms that can diminish unit efficiency gains when combined (Ambec *et al.*, 2013; J. Wang *et al.*, 2023; Zhang *et al.*, 2024). The negative sign pattern for the coefficient(s) associated with the governance variable slightly diminish (-0.014), providing insight into the fact that once the joint mechanism was recognised, governance can lead to reductions in emissions even when automation is not the primary margin of adjustment.

From the research and practices there are three general messages. The first, is that robotics shows a stable reducing relationship with CO2 emissions ranging from -0.026 to -0.050. This consistent pattern suggests that focused automation investment in the most energy-intensive segments of the economy allows processes to be upgraded and green innovations in supply chains to be achieved which lead to a reduction in CO2 emissions. Secondly, the relationship between GDP and CO2 is not linear in nature, as indicated by the existence of an estimated turning point found within the scope of the data. The turning point is in accordance with the trajectory in the provinces where they industrialised and subsequently reduced CO2 emissions by increasing the scale of capital, services, and regulation. Thirdly, the design of governance affects the ability to lock in absolute reductions in CO2 emissions. The overall pattern shows that as the emphasis of governance shifts from input-based and compliance-based governance, to governance that focuses on outcomes, the combined impact of technology gains and the expansion effects created by automation will lead to a decrease in CO2 emissions. Therefore, the combination of the results supports creating a synergistic approach to achieving the greatest benefit. Therefore, to achieve the maximum benefit of technology for reducing CO2 emissions it is necessary to support the increased usage of automation in the most cost-effective sectors, design the governance structure to focus on outcomes instead of inputs, and to coordinate energy policy with the development of cleaner

energy and digital governance tools, so that the utilisation of technology to reduce CO2 emissions can be most effectively achieved.

4.4. *Checking robustness with Paris Winsten regression*

A Prais–Winsten regression test is used to validate the results of the FGLS method by virtue of the prior diagnostic work for the dataset. As shown in **Table 6**, the Prais-Winsten results continue to support the conclusion that the technological channel has a pathway towards emissions reductions. The coefficient on the penetration level of industrial robots in the Baseline Specification is -0.034, indicating a negative relationship between robot penetration and carbon dioxide produced per province. While fuels (energy) are still positively associated with carbon dioxide emissions and gross domestic product, labour and the number of industries add considerably less to those relationships, as shown by the coefficients. When examining the environmental governance index (E.G.I.) the coefficient is +0.032 for the environmental governance index. This is consistent with the view that although they may not provide immediate outcomes, governance efforts will increase when environmental pressures are highest. Furthermore, the Prais-Winsten regression results and findings indicate that in terms of emissions, an increase in automation results in a reduction in emissions intensity. Therefore, there is strong evidence that the results from China and from the cross-country research line support the findings of this research (J. Wang *et al.*, 2023).

Table 6. Prais-Winsten regression estimates.

Variables	Baseline	Non-Linear	Interaction term
	Column (1)	Column (2)	Column (3)
RBT	−0.034***	−0.031***	−0.059**
	(−4.08)	(−3.81)	(−2.07)
ENV_GOV	0.032*	0.024**	−0.004
	(1.65)	(2.18)	(−0.05)
RBT × ENV_GOV	—	—	0.006**
			(2.42)
Energy	0.083***	0.080***	0.084***
	(4.34)	(4.23)	(4.40)
GDP	0.129**	4.520***	0.149***
	(2.25)	(3.75)	(2.60)
GDP^2	—	−0.481***	—
		(−3.74)	
Labor	0.015	0.022**	0.016
	(1.40)	(1.98)	(1.42)
IND	0.004	0.003	0.004
	(0.76)	(0.59)	(0.78)
Constant	3.515***	−6.454**	3.569***
	(13.66)	(−2.31)	(9.68)
Wald χ^2	0.9842	0.9852	0.9843
Prob > χ^2	45.21	61.44	48.06
Observations	0.000	0.000	0.000

*Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%. T-values are presented in brackets.*

This cross-sectional study reinforces the EKC hypothesis by measuring nonlinear income effects. The linearity of the GDP term (4.520) and the squared GDP term (−0.481) demonstrates an inverse U relationship with emissions that increase during early stages of development before declining when the use of cleaner capital, services and regulatory capacity has been fully developed. This finding is consistent with long-standing evidence supporting the EKC hypothesis for China, as well as with global studies showing that as countries experience increased income levels, they also tend to exert less environmental pressure. The robotics channel, which has a continually negative coefficient (−0.031), supports the theory that as robots and digital controls are being used more frequently in the processes of production and delivery, this will continue to decrease greenhouse gas emissions after considering any nonlinearities in income level. The governance coefficient also remains positive (0.024), which implies that provinces with the highest levels of environmental degradation (i.e., pollution), are where most of the institutional inputs and policy campaigns take place (Jianxun Yang *et al.*, 2024). Taken together, the results from Prais-Winsten's estimation of the nonlinear component of the analysis reaffirm the EKC hypotheses, while at the same time preserving the central important role of robots in bending emissions downward as provinces advance into higher income, cleaner technology regimes. The introduction of an interaction term to represent how policy context affects the technology effect offers additional clarity and evidence on the relationship between robot diffusion and lower CO_2 emissions. The direct coefficient for the robotics channel has become even more negative (−0.059) than previously reported. The interaction term between governance and robotics has a positive coefficient (0.006). Therefore, the

carbon savings from robots will be diminished somewhat by the increasing governance intensity for different provinces. This pattern is consistent with other studies that have examined these issues in large industrial hubs where strict governance and rapid automation have developed simultaneously. In those circumstances, the efficiencies achieved from robot automation are partially offset by the simultaneous growth of scale of production and by compliance with stricter regulations that create higher levels of activity. The governance coefficient, which does not refer to combined impacts, has dropped substantially (−0.004). Therefore, when one takes into account the combined effects of the interaction term with robotics, the overall impact of governance on CO_2 emissions has not been found to be positive or beneficial. There are other recent studies that support the findings of this research which have shown that the carbon effect of digital and robotic upgrades is dependent upon the design of policies and the signals provided by the market (Lin *et al.*, 2024). In order to capture all carbon benefits of improved efficiency and to ensure the benefits are not diminished by rebound effects at the system-wide level, it is important to align the governance structure towards outcome-based instruments.

4.5. *Regional level sub-group analysis*

There could have been different effects of governance and artificial intelligence to influence the carbon emissions in central and eastern regions, and western regions. **Table 7** shows that industrial robots have a slightly positive effect on carbon emissions in the central and eastern regions. However, as industrial robots are integrated into already established and intensive industrial networks, the efficiency and output increase that come from improved utilisation could outweigh the additional carbon emissions resulting from throughput. In addition, the western region shows a large inverse coefficient on the carbon emissions resulting from robots at −0.046. This suggests that western countries have been utilising robots primarily for updates and upgrades to their processes, as well as an increase in energy efficiency, with relatively little to no offsetting scale effects. The same is true for environmental governance. While governance systems are somewhat more visible in areas of higher environmental concern, as indicated by 0.018 for the central–eastern regions and 0.019 for the western regions, the primary driver of emissions in both regions is increased energy use. The central–eastern regions have much higher sensitivity to energy use than the western regions, with a coefficient of 0.188 compared to 0.059 for the west, due to the coastal regions being far more dependent on energy for manufacturing and on urban areas that are densely populated. The income variables tell a different story regarding development.

Table 7. Regional level sub-group analysis.

Variables	Central and Eastern Regions	Western Regions
	Column (1)	Column (2)
RBT	0.007***	−0.046***
	(3.53)	(−44.73)
ENV_GOV	0.018***	0.019***
	(5.53)	(12.85)
Energy	0.188***	0.059***
	(16.83)	(53.04)
GDP	−0.066***	0.162***
	(−6.48)	(11.34)
Labor	0.009**	0.021***
	(2.57)	(5.85)
IND	0.002	0.004***
	(1.27)	(2.70)
Constant	3.837***	3.521***
	(59.14)	(58.06)
Wald χ^2	354.85	4324.01
Prob > χ^2	0.000	0.000
Observations	192	288
Groups (provinces)	12	18

*Note: *, **, and *** indicate the significance level at 10%, 5%, and 1%. T-values are presented in brackets.*

In the central–eastern regions, GDP has a coefficient of -0.066, indicating a more significant focus on cleaner sources of investment capital and services and greater enforcement of environmental standards; while, in the western regions, GDP has a coefficient of 0.162, indicating an earlier stage of industrialisation where growth will still result in increased emissions. Labor contributes to the increase in emissions in both regions, although to a greater extent in the western regions with a coefficient of 0.021, compared to a coefficient of 0.009 for labour from the central–eastern regions. This suggests that employment growth in the western regions is related to a continued reliance on energy and material-intensive activities. There is virtually no effect of industrialisation on carbon emissions in the central–eastern regions, with a coefficient of 0.002, while industrialisation does have a positive effect

on carbon emissions in the western regions, with a coefficient of 0.004, due to the differences in the stages of transition along the path to structural transformation. Therefore, this suggests a need to develop specific and targeted policies for these regions. In the western region, it may be beneficial to combine robotics and energy-efficiency improvements to achieve immediate carbon reductions without major rebounds. Conversely, in the central–east regions, the pairing of automation with carbon reduction-based incentives would better ensure that efficiency gains convert to absolute emissions reductions. In conclusion, while the potential exists to use technology as a means of reducing carbon emissions in both regions, the carbon dividends of using this lever will depend primarily on the local conditions and how scale, structure, and enforcement intersect and interact. These conditions differ consistently between China's coastal regions and the inland provinces that are attempting to "catch up" to the coastal regions.

5. Conclusions and policy implications

This paper aims to examine the impact of industrial robots and environmental governance on carbon emissions in China based on data from thirty Chinese provinces spanning from 2007~2022. The paper identifies factors influencing carbon emissions across the thirty provinces using the method of FGLS and Prais-Winsten after performing a number of pre-diagnostic tests for cross section dependency, slope heterogeneity, and serial correlation. The findings are consistent in showing that industrial robots lead to a decrease in carbon emissions when the results are considered holistically, suggesting that industrial robots may create a technological channel of reduction through process upgrade and production optimisation of energy efficiency. Furthermore, the results indicate a positive association between the Environmental Governance index and high-pressure regulatory environments in linear models. This suggests that Environmental Governance metrics may reflect both mobilised policy and administrative attention in situations with the greatest challenges rather than immediate tangible results; however, this positive association is partially diminished when the interaction/relationship with technology is incorporated. Energy consumption continues to represent the single most significant proximate driver of carbon emissions, but the roles of economic scale, labour and industrial structure in driving emissions change or strengthen as industrial development continues. Importantly, the regional evidence shows that the carbon dividend from automation is not uniform: it is strongest where scale effects are smaller and production systems are earlier in the upgrading cycle, and it is weaker where dense industrial ecosystems can offset efficiency with throughput. Overall, the study concludes that technology-led abatement is viable but context dependent, and that governance contributes most when it is aligned with how firms adopt and operate cleaner technologies rather than with policy inputs alone.

The findings of this study bring several policy implications for policymakers. First, lock in technology's carbon dividend with outcome-based governance. Set annual, sector-by-province carbon targets for the top emitting industries; require real-time digital monitoring, reporting, and verification for large plants; tie permits, subsidies, and concessional credit to verified emission reductions rather than compliance inputs; mandate clean-power procurement contracts for major electricity users adopting automation; and make ISO-style energy-management systems and third-party energy audits a prerequisite for any public support. Second, scale robot-enabled retrofits exactly where the marginal abatement is highest. Launch a dedicated "Robots for Reduction" facility offering performance-based tax credits per tonne of CO_2 avoided and 8–10-year concessional loans for upgrades in steel, cement, chemicals, equipment manufacturing, and food processing. Require pre/post retrofit energy audits, minimum efficiency standards (high-efficiency motors, variable-speed drives), waste-heat recovery on kilns and dryers, predictive-maintenance programs, and sub-metering at line level. Create SME vouchers to cover engineering design and commissioning and give public-procurement preference to products made in verified low-carbon lines. Third, tailor instruments to regional realities. In western provinces, fast-track automation in industrial parks with plug-and-play clean electricity, on-bill financing for retrofits, shared robotics testbeds, and targeted grid upgrades to absorb additional renewable power. Lastly, central authorities are required to develop standardised metrics to evaluate environmental governance performance in context of the digital transformation. There should be national level monitoring framework that may track progress and ensure an effective accountability. It is suggested to align digital innovation with robust governance framework for having the full potential of green investments in digital economy.

Competing interests' statement

There are not any known competing interests among the authors of this study.

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Data availability statement

The data will be made available on reasonable request.

References

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of political economy*, *128*(6), 2188-2244.

Ambec, S., Cohen, M. A., Elgie, S., & Lanoie, P. (2013). The Porter hypothesis at 20: can environmental regulation enhance innovation and competitiveness? *Review of environmental economics and policy*.

Azimi, M., & Bian, Z. (2023). Provincial and regional analysis of carbon neutrality policy and the environmental Kuznets curve: examining their effect on CO2 emissions in China. *Environmental Science and Pollution Research*, *30*(16), 46234-46247.

Bai, J., Liao, Y., & Wang, X. (2021). Panel Data Models with Cross-Sectional Dependence: A Selective Review. *Econometrics*

Journal, *24*(3), 353-381. https://doi.org/10.1093/ectj/utaa029

Beck, N., & Katz, J. N. (1995). What To Do (and Not to Do) with Time-Series Cross-Section Data. *American Political Science Review*, *89*(3), 634-647. https://doi.org/10.2307/2082979

Bersvendsen, T., & Ditzen, J. (2021). A New Approach to Test for Slope Heterogeneity in Panels with Cross-Sectional Dependence. *Journal of Applied Econometrics*, *36*(4), 483-501. https://doi.org/10.1002/jae.2816

Chen, F., & Liu, W. (2025). Does Industrial Robot Adoption Reduce Pollution Emission? Evidence from China. *Sustainability*, *17*(13), 6202.

Chen, S.-C., Chen, H.-M., Chen, H.-K., & Li, C.-L. (2024). Multi-objective optimization in Industry 5.0: Human-centric AI integration for sustainable and intelligent manufacturing. *Processes*, *12*(12), 2723.

Chen, Y., Xu, W., Zhou, Q., & Zhou, Z. (2020). Total factor energy efficiency, carbon emission efficiency, and technology gap: Evidence from sub-industries of Anhui province in China. *Sustainability*, *12*(4), 1402.

Chudik, A., & Pesaran, M. H. (2015). Common correlated effects estimation of heterogeneous dynamic panel data models with weakly exogenous regressors. *Journal of Econometrics*, *188*(2), 393-420.

Ditzen, J. (2018). Estimating dynamic common-correlated effects in Stata. *The stata journal*, *18*(3), 585-617.

Drukker, D. M. (2003). Testing for serial correlation in linear panel-data models. *The stata journal*, *3*(2), 168-177.

Dumitrescu, E.-I., & Hurlin, C. (2012). Testing for Granger non-causality in heterogeneous panels. *Economic modelling*, *29*(4), 1450-1460.

Fan, Y., Liao, Y., & Min, Q. (2015). A New Approach to Testing for Weak Cross-Sectional Dependence with Large Panel Data. *Journal of Econometrics*, *186*(1), 124-131. https://doi.org/10.1016/j.jeconom.2014.11.004

Fang, X., & Liu, M. (2024). Facilitation or inhibition? Government environmental attention and corporate green technology innovation. *Journal of Environmental Planning and Management*, 1-43.

Farrar, D. E., & Glauber, R. R. (1967). Multicollinearity in regression analysis: the problem revisited. *The review of economic and statistics*, 92-107.

Fischer, C., Qu, C., & Goulder, L. H. (2024). *Rate-Based Emissions Trading with Overlapping Policies: Insights from Theory and an Application to China*.

Graetz, G., & Michaels, G. (2018). Robots at work. *Review of economics and statistics*, *100*(5), 753-768.

Grossman, G. M., & Krueger, A. B. (1995). Economic growth and the environment. *The quarterly journal of economics*, *110*(2), 353-377.

Gu, X., & Qiao, S. (2024). Break the eclectic choice: Can green credit policy restraint the polluting firms' financialization? Evidence from China. *SAGE Open*, *14*(4), 21582440241288063.

Guo, B., Feng, W., & Lin, J. (2024). The effect of industrial upgrading on energy consumption. *Energy Strategy Reviews*, *54*, 101451.

Guo, X., & Pang, J. (2023). Analysis of provincial CO2 emission peaking in China: Insights from production and consumption. *Applied Energy*, *331*, 120446.

Ha, L. T. (2024). An investigation of dynamic connectedness between robotic, artificial intelligence development, and carbon risk by quantile spillovers. *Clean Technologies and Environmental Policy*, *26*(9), 3051-3067.

Han, W.-Z., & Zhang, Y.-M. (2024). Carbon reduction effect of industrial robots: Breaking the impasse for carbon emissions and development. *Innovation and Green Development*, *3*(3), 100158.

Hansen, B. E. (2007). Least Squares Model Averaging. *Econometrica*, *75*(4), 1175-1189. https://doi.org/10.1111/j.1468-0262.2007.00785.x

He, J., & Wang, H. (2012). Economic structure, development policy and environmental quality: An empirical analysis of environmental Kuznets curves with Chinese municipal data. *Ecological economics*, *76*, 49-59.

Hu, J., Xiao, D., Li, B., & Peng, L. (2025). Environmental Information Disclosure and Firms' Green Total Factor Productivity: Evidence from New Ambient Air Quality Standards in China. *Atmosphere*, *16*(2), 155.

Huang, X., Wu, X., Guo, X., & Shen, Y. (2024). Agricultural carbon emissions in China: measurement, spatiotemporal evolution, and influencing factors analysis. *Frontiers in Environmental Science*, *12*, 1488047.

Huang, Y., Chen, Z., Li, H., & Yin, S. (2023). The impact of digital economy on green total factor productivity considering the labor-technology-pollution factors. *Scientific Reports*, *13*(1), 22902.

ICAP. (2024). China National ETS. In: International Carbon Action Partnership.

IEA. (2017). *Digitalisation and Energy*

IEA. (2024). *CO_2 Emissions in 2023*. International Energy Agency (Global Energy Review).

IFR. (2024). *World Robotics 2024 Report*. International Federation of Robotics.

IPE. (2021/2024). *Welcome to the Blue Map: Protect Green Development, Protect our Planet*. Institute of Public & Environmental Affairs. https://wwwen.ipe.org.cn/

Jin, W. (2024). Unveiling the impact of industrial robots on consumption-based embodied carbon intensity: A global perspective. *Energy Strategy Reviews*, *54*, 101484.

Juodis, A., & Reese, S. (2021). Cross-sectional dependence robust inference in panel data models with a factor structure. *Journal of Econometrics*, *220*(2), 383-400. https://doi.org/10.1016/j.jeconom.2020.09.001

Karplus, V. J., & Wu, M. (2023). Dynamic responses of SO2 pollution to China's environmental inspections. *Proceedings of the National Academy of Sciences*, *120*(17), e2214262120.

Karplus, V. J., & Zhang, D. (2023). Tensions between local interests and broader gains. *Nature Energy*, *8*(7), 651-652.

Karplus, V. J., Zhang, S., & Almond, D. (2018). Quantifying coal power plant responses to tighter SO2 emissions standards in China. *Proceedings of the National Academy of Sciences*, *115*(27), 7004-7009.

Kusiak, A. (2019a). Fundamentals of smart manufacturing: A multi-thread perspective. *Annual Reviews in Control*, *47*, 214-220.

Kusiak, A. (2019b). Intelligent manufacturing: bridging two centuries. *Journal of intelligent manufacturing*, *30*(1), 1-2.

Lan, J., Zhai, T., Sun, X., Liu, Z., & Lu, L. (2025). Environmental information disclosure and carbon emission efficiency:

Evidence from China. *International Review of Economics & Finance*, 104170.

LBNL. (2024). *Clean Industry in China: A Techno-Economic Comparison of Electrified Heat Technologies, Barriers, and Policy Options*.

Li, R., Wang, Q., & Guo, J. (2024). Revisiting the environmental Kuznets curve (EKC) hypothesis of carbon emissions: exploring the impact of geopolitical risks, natural resource rents, corrupt governance, and energy intensity. *Journal of environmental management*, *351*, 119663.

Li, T., Wang, Y., & Zhao, D. (2016). Environmental Kuznets curve in China: new evidence from dynamic panel analysis. *Energy Policy*, *91*, 138-147.

Li, X., & Gallagher, K. P. (2022). Assessing the climate change exposure of foreign direct investment. *Nature communications*, *13*(1), 1451.

Lin, S., Zhou, Z., Hu, X., Chen, S., & Huang, J. (2024). How can urban economic complexity promote green economic growth in China? The perspective of green technology innovation and industrial structure upgrading. *Journal of Cleaner Production*, *450*, 141807.

Lin, W., & Li, X. (2024). GRASNet: A novel graph neural network for improving human action recognition and well-being assessment in smart manufacturing. *Manufacturing Letters*, *41*, 1452-1463.

Liu, X., & Yang, X. (2022). Impact of China's environmental decentralization on carbon emissions from energy consumption: An empirical study based on the dynamic spatial econometric model. *Environmental Science and Pollution Research*, *29*(48), 72140-72158.

Liu, Y. (2023). Impact of industrial robots on environmental pollution: evidence from China. *Scientific Reports*, *13*(1), 20769.

Liu, Y., Wang, A., & Wu, Y. (2021). Environmental regulation and green innovation: Evidence from China's new environmental protection law. *Journal of Cleaner Production*, *297*, 126698.

Liu, Z., Li, L., Hou, J., & Li, B. (2025). Does digital innovation improve carbon productivity? A new perspective based on industrial upgrading. *Applied Economics*, 1-19.

Liu, Z., Tang, Y., Wilson, J., Tao, X., Lv, B., Wang, Z., Xu, Y., Zhang, Z., Zhang, Y., & Zhao, W. (2023). Influence of government attention on environmental quality: An analysis of 30 provinces in China. *Environmental Impact Assessment Review*, *100*, 107084.

Ma, Y., Zhang, Z., & Yang, Y. (2023). Calculation of carbon emission efficiency in China and analysis of influencing factors. *Environmental Science and Pollution Research*, *30*(51), 111208-111220.

Mahmood, H., Furqan, M., Hassan, M. S., & Rej, S. (2023). The environmental Kuznets Curve (EKC) hypothesis in China: A review. *Sustainability*, *15*(7), 6110.

MEE. (2024). *Progress Report of China's National Carbon Market*. Ministry of Ecology and Environment of China.

Mi, Z., & Sun, X. (2021). Provinces with transitions in industrial structure and energy mix performed best in climate change mitigation in China. *Communications Earth & Environment*, *2*(1), 182.

Mittal, S., Khan, M. A., Purohit, J. K., Menon, K., Romero, D., & Wuest, T. (2020). A smart manufacturing adoption framework for SMEs. *International Journal of Production Research*, *58*(5), 1555-1573.

Mu, C., Li, K., Liu, S., Wei, Y., Mu, M., Shang, X., Liu, F., Zhang, C., Liu, H., & Gao, T. (2025). Recent intensified riverine CO2 emission across the Northern Hemisphere permafrost region. *Nature communications*, *16*(1), 3616.

Musah, M., Kong, Y., Mensah, I. A., Antwi, S. K., Osei, A. A., & Donkor, M. (2021). Modelling the connection between energy consumption and carbon emissions in North Africa: Evidence from panel models robust to cross-sectional dependence and slope heterogeneity. *Environment, Development and Sustainability*, *23*(10), 15225-15239.

NBS. (2025). *Investment in Fixed Assets from January to May 2025*.

O'brien, R. M. (2007). A caution regarding rules of thumb for variance inflation factors. *Quality & Quantity*, *41*(5), 673-690.

Pesaran, M. H. (2015). Testing Weak Cross-Sectional Dependence in Large Panels. *Econometric Reviews*, *34*(6-10), 1089-1117. https://doi.org/10.1080/07474938.2014.956623

Pesaran, M. H. (2015). *Time series and panel data econometrics*. Oxford University Press.

Pesaran, M. H., Schuermann, T., & Weiner, S. M. (2004). Modeling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business & Economic Statistics*, *22*(2), 129-162.

Pesaran, M. H., & Xie, Z. (2021). Testing for Slope Heterogeneity in Large Panels. *Journal of Econometrics*, *212*(2), 517-544. https://doi.org/10.1016/j.jeconom.2019.07.007

Pesaran, M. H., & Yamagata, T. (2008). Testing slope homogeneity in large panels. *Journal of Econometrics*, *142*(1), 50-93.

Prais, S. J., & Winsten, C. B. (1954). *Trend estimators and serial correlation*.

Ren, F. (2024). Does Government Environmental Concern Affect Enterprise Sustainable Development? Evidence from China. *Sustainability*, *16*(21), 9527.

Reuters. (2024). China cuts carbon intensity in 2024 but still lags on key targets.

Sarkodie, S. A., & Strezov, V. (2019). A review on environmental Kuznets curve hypothesis using bibliometric and meta-analysis. *Science of the Total Environment*, *649*, 128-145.

Shan, Y., Guan, D., Zheng, H., Ou, J., Li, Y., Meng, J., Mi, Z., Liu, Z., & Zhang, Q. (2018). China CO2 emission accounts 1997–2015. *Scientific data*, *5*(1), 1-14.

Shan, Y., Huang, Q., Guan, D., & Hubacek, K. (2020). China CO2 emission accounts 2016–2017. *Scientific data*, *7*(1), 54.

Shen, L., Qian, W., & Yang, Y. (2024). The divergence and driving factors of corporate environmental information disclosure in China. *Environmental Research Communications*, *6*(7), 075029.

Shiyi, C., & Dengke, C. (2022). On Accelerating the Green and Low-Carbon: Transition for an Ecological Civilization With Chinese Characteristics. *China Economist*, *17*(2), 28-47.

Song, W., Han, X., & Liu, Q. (2024). Patterns of environmental regulation and green innovation in China. *Structural Change and Economic Dynamics*, *71*, 176-192.

Stern, D. I. (2004). The rise and fall of the environmental Kuznets curve. *World development*, *32*(8), 1419-1439.

Tan, S., Li, W., Liu, X., Wang, Y., & Wang, M. (2024). Exploring paths underpinning the implementation of municipal waste sorting: Evidence from China. *Environmental Impact Assessment Review*, *106*, 107510.

Terry, S., Lu, H., Fidan, I., Zhang, Y., Tantawi, K., Guo, T., & Asiabanpour, B. (2020). The influence of smart manufacturing

towards energy conservation: a review. *Technologies*, *8*(2), 31.

Wang, J., Wang, W., Liu, Y., & Wu, H. (2023). Can industrial robots reduce carbon emissions? Based on the perspective of energy rebound effect and labor factor flow in China. *Technology in Society*, *72*, 102208.

Wang, M., & Feng, C. (2018). Investigating the drivers of energy-related CO2 emissions in China's industrial sector: From regional and provincial perspectives. *Structural Change and Economic Dynamics*, *46*, 136-147.

Wang, Q., Wang, X., Li, R., & Jiang, X. (2024). Reinvestigating the environmental Kuznets curve (EKC) of carbon emissions and ecological footprint in 147 countries: a matter of trade protectionism. *Humanities and Social Sciences Communications*, *11*(1), 1-17.

Wang, Q., Yang, T., & Li, R. (2023). Does income inequality reshape the environmental Kuznets curve (EKC) hypothesis? A nonlinear panel data analysis. *Environmental Research*, *216*, 114575.

Wang, Q., Zhang, Y., & Li, R. (2025). Achieving Sustainable Development: Bridging Economic Growth and Environmental Resilience Through EKC and LCC. *Sustainable Development*.

Wang, S., Wang, H., Zhang, L., & Dang, J. (2019). Provincial carbon emissions efficiency and its influencing factors in China. *Sustainability*, *11*(8), 2355.

Wang, X., Liu, M., Liu, C., Ling, L., & Zhang, X. (2023). Data-driven and Knowledge-based predictive maintenance method for industrial robots for the production stability of intelligent manufacturing. *Expert Systems with Applications*, *234*, 121136.

Wei, C. (2024). Historical trend and drivers of China's CO2 emissions from 2000 to 2020. *Environment, Development and Sustainability*, *26*(1), 2225-2244.

Wei, L., & Wang, Z. (2022). Differentiation Analysis on Carbon Emission Efficiency and Its Factors at Different Industrialization Stages: Evidence from Mainland China. *International Journal of Environmental Research and Public Health*, *19*(24), 16650.

Wooldridge, J. M. (2003). Cluster-sample methods in applied econometrics. *American economic review*, *93*(2), 133-138.

Wu, Q., & Gu, S. (2021). Exploring the focus of future CO2 emission reduction in China's industrial sectors. *Greenhouse Gases: Science and Technology*, *11*(4), 682-696.

Xie, F., Guan, X., Zhu, J., Ruan, J., Wang, Z., & Liu, H. (2023). Environmental protection goes digital: a policy perspective on promoting digitalization for sustainable development in China. *Sustainability*, *15*(13), 10673.

Xu, H., Li, G., & Chen, B. (2025). Environmental vertical management reform and data manipulation in the public sector: evidence from China. *Journal of Public Policy*, *45*(1), 68-96.

Yang, J., Deng, J., Ye, L., Liu, L., & Hu, X. (2024). Study on the impact of central environmental protection inspection on the health of the older adult population—A quasi-natural experiment in China. *Frontiers in Public Health*, *12*, 1290192.

Yang, J., Wang, Q., & Huang, Y. (2024). Environmental vertical management reform and firms' ESG performance: evidence from China. *Humanities and Social Sciences Communications*, *11*(1), 1-13.

Yang, J., Zhao, Z., Fang, W., Ma, Z., Liu, M., & Bi, J. (2024). China's progress in synergetic governance of climate change and multiple environmental issues. *PNAS nexus*, *3*(9), pgae351.

Yang, L., Liu, Y., & Deng, H. (2023). Environmental governance, local government competition and industrial green transformation: Evidence from China's sustainable development practice. *Sustainable Development*, *31*(2), 1054-1068.

Yang, X., Zhu, N., Lv, J., & Luo, S. (2025). Industrial robot applications' effects on consumption of energy and its spatial effects. *Environment, Development & Sustainability*, *27*(6).

Yao, W., Liu, L., Fujii, H., & Li, L. (2024). Digitalization and net-zero carbon: The role of industrial robots towards carbon dioxide emission reduction. *Journal of Cleaner Production*, *450*, 141820.

Ye, Y., Yang, X., & Shi, L. (2023). Environmental information disclosure and corporate performance: Evidence from Chinese listed companies. *Heliyon*, *9*(12).

Yu, L., Wang, Y., Wei, X., & Zeng, C. (2023). Towards low-carbon development: The role of industrial robots in decarbonization in Chinese cities. *Journal of environmental management*, *330*, 117216.

Zhang, C., & Lin, Y. (2012). Panel estimation for urbanization, energy consumption and CO2 emissions: A regional analysis in China. *Energy Policy*, *49*, 488-498.

Zhang, W., Zhu, B., Li, Y., & Yan, D. (2024). Revisiting the Porter hypothesis: a multi-country meta-analysis of the relationship between environmental regulation and green innovation. *Humanities and Social Sciences Communications*, *11*(1), 1-15.

Zhang, X., & Zhu, H. (2023). The impact of industrial intelligence on carbon emissions: Evidence from the three largest economies. *Sustainability*, *15*(7), 6316.

Zhao, X., Ding, X., & Li, L. (2021). Research on environmental regulation, technological innovation and green transformation of manufacturing industry in the Yangtze River Economic Belt. *Sustainability*, *13*(18), 10005.

Zheng, X., Wang, J., Xu, X., Yu, R., & Zhang, S. (2024). Carbon Kuznets curve in China: Nighttime light analysis in prefecture-level cities. *Heliyon*, *10*(16).

Zheng, Y., Wang, M., Ma, X., Zhu, C., & Gao, Q. (2024). The Dynamic Relationship Between Industrial Structure Upgrading and Carbon Emissions: New Evidence from Chinese Provincial Data. *Sustainability*, *16*(22), 10118.

Zhou, D. (2020). China's environmental vertical management reform: An effective and sustainable way forward or trouble in itself? *Laws*, *9*(4), 25.

Zhou, Y., Xu, Y., Liu, C., Fang, Z., Fu, X., & He, M. (2019). The threshold effect of China's financial development on green total factor productivity. *Sustainability*, *11*(14), 3776.

Zhu, H., Sang, B., Zhang, C., & Guo, L. (2023). Have industrial robots improved pollution reduction? A theoretical approach and empirical analysis. *China & World Economy*, *31*(4), 153-172. .