

## Article

# Global Value Chain Embedding and Low-Carbon Innovation Transition: A Sustainable Development Perspective on Carbon-Intensive Industries

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## Abstract

The innovation-driven transformation of carbon-intensive industries is central to global climate governance and sustainable industrial specialization. Integrating Global Value Chain (GVC) embedding, external environmental dynamics, and industrial innovation, this study utilizes micro-to-macro extracted panel data from China's carbon-intensive industries from 2007 to 2023 to construct a double debiased machine learning (DDML) model. We identify a robust innovation-promoting effect driven by both GVC participation and the GVC Domestic Content Ratio (DCR). Employing a causal mediation framework, we reveal that GVC embedding indirectly drives innovation by reshaping four functional dimensions: upgrading intermediate export quality, stimulating technology market activity, internalizing climate policy uncertainty, and aligning environmental violation disclosure. Furthermore, structural heterogeneity tests demonstrate that mature resource-based cities and backward-linked industries benefit substantially from learning-by-doing effects. In contrast, forward-linked industries and non-mature cities face an elevated risk of a positioning paradox and comparative advantage lock-in. This study provides rigorous empirical evidence for advancing SDG 9 in developing economies seeking to reconcile deeper global economic integration with carbon neutrality objectives.

**Keywords:** industrial innovation; carbon-intensive industry; global value chain; global economic integration; sustainable development

## 1. Introduction

The rapid increase in greenhouse gas emissions poses a substantial threat to global ecosystems and human well-being. As major contributors to global emissions, the green transformation of carbon-intensive industries is essential for achieving the mitigation targets of the Paris Agreement [1]. However, the existing international division of labor within global production systems has intensified challenges such as carbon leakage and competitive inequities in climate governance [2]. Developed economies tend to relocate carbon-intensive production activities to developing countries through global production networks, exacerbating carbon leakage and reinforcing high-carbon lock-in in host economies. Furthermore, implementing unilateral climate policy instruments, such as the EU Carbon Border Adjustment Mechanism, while aiming to internalize carbon costs, may further amplify North–South conflicts over emission responsibilities and complicate the global allocation of carbon-intensive industries [3]. Consequently, fostering innovation-driven green upgrading of carbon-intensive sectors in developing countries has emerged as a central challenge for achieving equitable and effective post-Paris Agreement climate governance.



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The ongoing restructuring of global value chains (GVCs) offers a potential pathway to align international industrial specialization with global carbon governance [4]. The diffusion of digital technologies and the tightening of environmental standards are accelerating the transmission of technology, knowledge, and green norms along GVCs. Developed economies continue to dominate high-value-added segments of GVCs by virtue of their advantages in R&D and green technologies, while developing economies can access low-carbon technologies and advanced management practices through deeper GVC participation. Such interactions can help transform international carbon cost pressures into incentives for industrial upgrading, thereby enabling carbon-intensive industries to escape high-carbon lock-in [5]. Additionally, enhanced cross-border coordination within GVCs provides an institutional platform for mitigating conflicts arising from unilateral climate policies, promoting a more inclusive and cooperative trajectory for low-carbon industrial development.

To address these issues, this study employed panel data from 270 Chinese cities between 2007 and 2023 to construct a double debiased machine learning (DDML) model. This model integrated GVC embedding, urban external environment, and innovative behavior in carbon-intensive industries, examining their relationships using a double debiased machine learning (DDML) algorithm. The objectives of this study included identifying the innovation effect of GVC embedding on urban carbon-intensive industries, clarifying the mechanisms through which GVC embedding shapes industrial innovation, and investigating the heterogeneity of GVC-driven innovation dividends across various industrial types and stages of urban development.

This study makes three marginal contributions. Theoretically, this study integrated GVC embedding, external environmental conditions, and industrial innovation within a unified framework; the model conceptualizes urban industrial innovation as a dynamic knowledge-processing system activated by information flows from multiple environmental dimensions, thereby elucidating nonlinear mechanisms through which GVC embedding translates external environmental reconfigurations into innovation outcomes. Methodologically, different from conventional GVC-innovation research that relies on macro-level multi-regional input–output (MRIO) tables, this study extracts industry-level GVC indicators from disaggregated customs transaction records. This micro-to-macro extraction approach mitigates aggregation bias inherent in MRIO-based analyses and enables granular identification of industry-level heterogeneity in GVC participation patterns—a methodological innovation that bridges the gap between micro-level trade dynamics and macro-level GVC measurement. Empirically, this study systematically identifies four environmental pathways—intermediate export quality upgrading, technology market activation, climate policy uncertainty internalization, and environmental enforcement alignment—while uncovering systematic asymmetries across embedding modes, industrial types, urban development stages, and participation modalities, thereby providing robust empirical foundations for designing innovation-driven upgrading strategies that reconcile deeper global economic integration with carbon neutrality objectives.

## 2. Literature Review and Theoretical Analysis

### 2.1. Literature Review

Against the backdrop of profound GVC restructuring and a rapidly evolving external environment, GVC embedding, external dynamics, and industrial transformation have garnered growing scholarly attention. Existing studies can be broadly classified into two strands. The first strand focuses on the impacts of GVC participation on firms and industries. At the micro level, GVC embedding enables lead firms to transmit knowledge spillovers and enforce technical standards, thereby incentivizing innovation in high-tech

firms and improving energy efficiency in medium-sized enterprises [6,7]. From the macro aspect, empirical evidence points to the heterogeneous effects of GVC participation and positional upgrading on industrial innovation. While deeper GVC participation generally enhances innovation efficiency, occupying higher positions within GVCs may exert an opposite effect [8–10].

The second strand of literature emphasizes the role of external environmental dynamics in shaping firm development and transformation. Specifically, the external environment influences the competitiveness of enterprise clusters through selection–retention mechanisms. Technological innovation networks can enhance energy efficiency via scale effects, whereas insufficient internal–external collaboration may hinder green development [11–13]. Furthermore, the alignment between the external knowledge environment and firms’ internal absorptive capacity is critical for innovation performance. External synchronicity promotes innovation by strengthening internal coordination, while digital transformation enhances ESG performance within external governance contexts [14–16].

Finally, research on industrial transformation has gradually shifted from linear to nonlinear and interactive frameworks. Classical theories emphasize technological innovation as the primary driver of industrial upgrading through technology introduction, architectural innovation, and paradigm shifts [17]. However, more recent studies identify asymmetric short- and long-term relationships between sustainable innovation and industrial transformation [18]. In practice, lock-in effects and path dependence often constrain innovation efficiency, while firms’ strategic choices between breakthrough and incremental innovation—mediated by technology spillovers and green innovation—depend critically on external policy support and internal capability synergy [19–21].

Although existing studies have provided an important basis for the fundamental understanding of GVC embedding and industrial transformation, most of these studies have only examined the impact of GVC embedding on industries in isolation, without integrating industrial innovation with the shaping of the urban external environment. To address these deficiencies, this study constructs a framework that integrates GVC embedding with the external environment and conducts an empirical analysis of the direct and indirect impacts of GVC embedding on innovation in carbon-intensive industries.

## 2.2. Theoretical Analysis

### 2.2.1. Direct Effects Analysis

New economic growth theory [22] posits that knowledge spillovers, increasing returns, and innovation systems constitute the fundamental drivers of economic growth. In the context of deep GVC reconfiguration, international production networks have become the primary conduits for knowledge flow and technology diffusion. GVC embedding not only affects the efficiency of obtaining external knowledge but also influences the innovation performance of urban industries through the reconfiguration of regional innovation ecosystems [23]. For carbon-intensive industries, characteristics such as high energy consumption, substantial carbon emissions, and strong path dependence expose firms to stringent environmental constraints and escalating pressures for technological upgrading. GVC embedding functions as a critical structural force that initiates processes of creative destruction in industrial innovation by introducing advanced technical standards and facilitating access to heterogeneous information.

The impact of GVC embedding on innovation in urban carbon-intensive industries operates primarily through two channels: technological upgrading and information transmission. Technologically, participation in high-complexity GVC activities, such as trade in high-end intermediate goods, can compel domestic industries to comply with international environmental standards and technical specifications. This pressure accelerates the

phase-out of obsolete production capacity, promotes the adoption of cleaner production processes, and stimulates green technological innovation [21,24]. Such dynamics exemplify Schumpeter's creative destruction, whereby GVC embedding introduces new technological combinations that disrupt existing technological trajectories, weaken path dependence, and reorient industries toward innovation-intensive development. From an informational perspective, GVCs function as a global hub for industrial information, transmitting critical signals regarding international market demands, technological trends, and policy adjustments. Access to this information reduces uncertainty in industrial innovation and facilitates the recombination of heterogeneous knowledge elements, thereby fostering the generation of disruptive innovations [25]. For carbon-intensive industries, GVC embedding at the national and sectoral levels enables firms to acquire information on international carbon pricing, thereby optimizing production processes and advancing green technologies. Thus, this study proposes hypothesis 1:

**Hypothesis 1.** *GVC embedding generates a strictly positive marginal effect on the innovation output of urban carbon-intensive industries through the dual channels of global information amplification and innovation network optimizations.*

### 2.2.2. Indirect Effect Analysis

The innovation system theory is rooted in the new economic growth theory, transforming the concept of innovation from isolated activities at the company level to an interactive process embedded in institutional, market, and regulatory structures. Within this framework, this study expands the urban innovation system to four functional dimensions—export market structure, technological infrastructure, climate governance, and regulatory enforcement. These dimensions jointly determine the efficiency of converting knowledge generated by the GVC into innovation outputs. GVC embedding reshapes each dimension through different channels, and each reshaped dimension further promotes innovation in carbon-intensive industries through specific knowledge transfer mechanisms, thus forming a complete GVC embedding–mechanism influence–innovation output closed loop.

Export environment—upgrading of intermediate export quality (IEQ). Carbon-intensive industries occupy upstream positions in global production networks, supplying intermediate inputs rather than final consumer goods. Integration into high-end GVC segments requires compliance with stringent international environmental standards—including CBAM—imposing buyer-driven quality pressure that compels firms to internalize advanced technological standards [26,27]. This quality-upgrading process directly enhances innovation output through two sub-channels: absorbing codified technical standards improves firms' absorptive capacity for external knowledge recombination, and climbing the quality ladder necessitates process innovations that reduce emission intensity, generating patentable green technologies. GVC Domestic Content Ratio (DCR)—reflecting upstream specialization—imposes more stringent quality requirements than participation depth alone, as upstream firms must simultaneously satisfy multiple downstream buyers with demanding specifications. This asymmetry predicts that positional upgrading is a more potent driver of quality-driven innovation than participation deepening.

Technological environment—stimulating of technology market activity (TMA). GVC embedding facilitates technology market internationalization and open innovation ecosystem construction, enabling carbon-intensive industries to access green technology licenses and shorten innovation cycles [28]. Active technology markets directly increase innovation output by reducing search costs for externally available technologies, lowering transaction barriers for knowledge transfer, and creating price signals that guide R&D allocation toward high-demand green solutions. The transmission mechanisms diverge by GVC di-

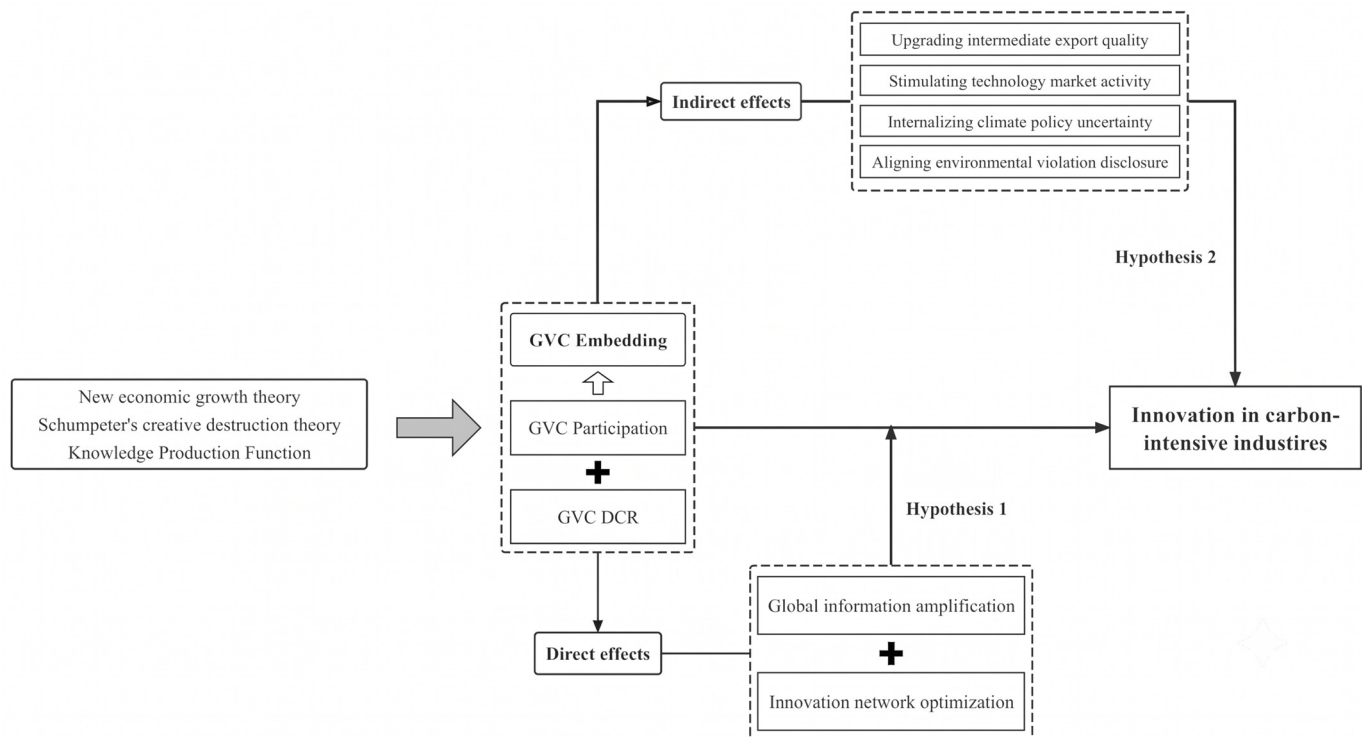
mension: participation activates technology markets through demand-pull—deeper trade integration generates immediate demand for external technology acquisition to meet buyer requirements [29]—while positioning operates through supply-side capability deepening, as upstream firms develop stronger internal R&D and absorptive capacity, enhancing selective knowledge integration [30]. The demand-pull channel generates more immediate market dynamics than gradual capability-building, predicting asymmetric coefficients between the two dimensions.

Climate environment—internalization of climate policy uncertainty (CPU). GVC embedding transmits international climate governance pressures to domestic cities, generating CPU as municipal governments recalibrate regulatory responses. For carbon-intensive industries, the operative channel is transition risk—regulatory and market uncertainty from evolving climate frameworks—rather than physical climate hazards [31,32]. CPU affects innovation output through a precautionary mechanism: regulatory uncertainty incentivizes firms to invest preemptively in cleaner technologies before binding regulations take effect, converting compliance risk into innovation drive. GVC participation intensifies regulatory volatility, paradoxically stimulating precautionary innovation as firms front-load clean technology investments. Conversely, GVC DCR reduces CPU: upstream specialization confers market power and technological autonomy, enabling proactive regulatory adaptation and making climate policy trajectories more predictable—thereby lowering the option value of waiting and encouraging sustained innovation investment. These opposing effects jointly determine climate-related innovation incentives.

Regulatory environment—alignment of environmental violation disclosure (EVD). GVC embedding reshapes regulatory enforcement dynamics that directly affect innovation incentives. Transparent and stringent EVD increases the expected cost of non-compliance, redirecting investment from emission-intensive production toward cleaner process innovation. GVC participation enhances regulatory transparency [33] yet generates race-to-the-bottom dynamics: competing jurisdictions strategically weaken enforcement to attract mobile capital [34], eroding the standards international governance frameworks promote, thereby dampening innovation incentives. In contrast, regulatory convergence characterizes GVC DCR: firms in higher value-chain positions derive competitive advantage from quality differentiation and compliance credibility rather than cost minimization, giving cities stronger incentives for rigorous enforcement that rewards compliant innovators. These asymmetric institutional effects illuminate GVC embedding's double-edged nature: participation intensity may erode enforcement standards through competitive arbitrage, while positional upgrading strengthens substantive regulatory compliance. Thus, this study proposes Hypothesis 2:

**Hypothesis 2.** *GVC embedding indirectly promotes urban carbon-intensive industry innovation by reshaping four environmental dimensions: upgrading intermediate export quality, stimulating technology market activity, internalizing climate policy uncertainty, and aligning environmental violation disclosure.*

The theoretical framework of this study is shown in Figure 1.



**Figure 1.** Theoretical framework.

### 3. Research Design

#### 3.1. Model Design

Given that the variables in this study span multiple dimensions, including country, city, and industry, and that high-dimensional confounding factors may exist, this study constructed a partial linear model within the DDML framework to estimate the net effect of GVC embedding on innovation output. This approach preserves the intuitive economic interpretation of GVC variables while capturing the nonlinear relationships between control variables and outcome variables. It effectively addresses endogeneity arising from model misspecification. This study identified the complex relationships between GVC embedding, the urban external environment, and innovation in carbon-intensive industries. By using residual instrumental variable regression, this study obtained the effective and unbiased estimator in Equation (1) [35]. The specific configuration of the algorithm architecture of the DDML model framework is shown in Table A1.

$$ICII_{it} = \theta_0 GVC\_Embed_{it} + g(X_{it}) + U_{it} \quad (1)$$

$$E(U_{it}|GVC\_Embed_{it}, X_{it}) = 0 \quad (2)$$

$$\hat{\theta}_0 = \left( \frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} GVC\_Embed_{it} \right)^{-1} \frac{1}{n} \sum_{i \in I, t \in T} \hat{V}_{it} (ICII_{it} - \hat{g}(X_{it})) \quad (3)$$

where  $ICII_{it}$  is the explained variable, representing the innovation output of carbon-intensive industries;  $GVC\_Embed_{it}$  is the explanatory variable, capturing both GVC participation and GVC DCR;  $\hat{g}(X_{it})$  is estimated using the DDML algorithm, with  $X_{it}$  representing a set of high-dimensional control variables;  $U_{it}$  denotes the error term, assumed to have a conditional mean of zero;  $\theta_0$  represents the estimation coefficient of primary interest;  $i$  indexes urban carbon-intensive industries; and  $t$  indexes time (years).

### 3.2. Variable Measurement

#### 3.2.1. Explained Variable

The value of patents was estimated using the patent renewal model proposed by [36], as specified in Equation (4). Two primary data sources were used: legal status updates of granted micro-invention patents from the State Intellectual Property Office and annual fee schedules for invention patents of different ages.

First, the distribution parameters were estimated using the generalized nonlinear least squares method:

$$y_{tj} = \phi^{-1}(1 - P_{tj}) = [c_{tj} - t \times \ln(1 - \delta_j) - \mu_j] / \sigma_j \quad (4)$$

where  $y_{tj}$  represents the survival condition of patent  $j$  at year  $t$ ,  $\phi^{-1}$  is the inverse of the standard normal cumulative distribution function,  $c_{tj}$  is the legal survival fee adjusted by CPI,  $\delta_j$  represents the technology depreciation rate, and  $P_{tj}$  follows a log-normal distribution  $\ln P_{tj} \sim N(\mu, \sigma^2)$ , where  $\mu$  and  $\sigma$  are the mean and standard deviation parameters of the lognormal distribution, respectively.  $P_{tj}$  represents the potential economic value of patent  $j$  in year  $t$ , and its distribution is endogenously determined by the patent renewal behavior—only when the expected revenue of the patent exceeds the renewal cost will the patent owner choose to renew it. Therefore, the renewal probability contains information about the patent value.

Second, a Monte Carlo simulation with 50,000 pseudorandom draws from the estimated log-normal distribution was conducted. Each realization was substituted into Equation (5) to derive the total patent value, producing a distribution of 50,000 values for each patent cohort. Age-specific weighting coefficients ( $V_1, V_2 \dots V_{20}$ ) were obtained by averaging patent values within the same age group, reflecting China's statutory maximum patent term of 20 years. To ensure measurement consistency, December 31 of each year was used as the observation point. Only invention patents that had been granted and were active on that date were included, avoiding double-counting of patents at different stages of their life cycle.

$$V(T) = \sum_{t=1}^{T^*} [R_{0j}(1 - \delta_j)^t - C_{tj}](1 + i)^{-t} \quad (5)$$

where  $R_{0j}$  denotes the base annual return of patent  $j$ , and  $i$  represents the risk-free rate.

Finally, patents were aggregated and weighted according to their respective city and industry classifications to derive the total patent value for each dimension in each year:

$$TV = \sum N_i \times V_i \quad (6)$$

where  $N_i$  denotes the number of valid invention patents of age  $i$  ( $i = 1, 2, \dots, 20$ ), and  $V_i$  is the simulated patent value coefficient for patents of age  $i$ .

The national total patent value in 2001 was normalized to 100, and a city-industry innovation index was calculated based on these weighted values.

#### 3.2.2. Explanatory Variable

To precisely capture the authentic division-of-labor position of city-level carbon-intensive industries within global production networks, this study abandons the conventional decomposition algorithm based on macro multi-regional input–output (MRIO) tables. The macro matrix decomposition approach is inherently constrained by data granularity, typically reflecting value-added flow characteristics only at the national or provincial level. Assigning national-level GVC indices uniformly to all cities within a given jurisdiction inevitably engenders severe ecological fallacy, obliterating the substantial spatial heterogeneity in openness and industrial capacity across cities. Such uniform assignment

implies the tacit assumption that all cities within a province share identical trade structures and GVC participation intensity—an assumption patently contradicted by the vast disparities in export orientation and industrial composition observed across Chinese cities. Therefore, this study adopts micro-level customs and industrial enterprise-matched data to reconstruct city-level GVC embedding measures from the bottom up.

Specifically, drawing on the micro-proportional allocation method widely recognized in international trade economics [37,38], this study rigorously distinguishes the destinations of firms' imported intermediates between export production and domestic sales. The core identification assumption posits that imported intermediates under processing trade are entirely allocated to export production as intermediate inputs, whereas imported intermediates under general trade are proportionally allocated between domestic sales and export production based on each firm's domestic-to-export revenue ratio. This distinction is critical because processing trade firms, by regulatory definition, import solely for re-export, while general trade firms serve both domestic and foreign markets, necessitating a scientifically grounded allocation of their imported inputs.

Building on this core assumption, the export domestic value-added ratio (DVAR) and its complement, the foreign value-added ratio (FVAR), are first computed at the micro firm level. Consider firm  $i$  belonging to industry  $k$  in city  $c$  at time  $t$ . The total value added embedded in firms' exports, denoted as  $VA_{ict}$ , equals the sum of domestic value added in exports ( $DVA_{ict}$ ) and foreign value added in exports ( $FVA_{ict}$ ):

$$VA_{ict} = DVA_{ict} + FVA_{ict} \quad (7)$$

where  $FVA_{ict}$  is decomposed according to trade regime. For processing trade imports, the entirety is allocated to export production:

$$FVA_{ict}^{proc} = M_{ict}^{proc} \quad (8)$$

where  $M_{ict}^{proc}$  denotes firm  $i$ 's imported intermediates under processing trade. For general trade imports, the proportional allocation rule applies:

$$FVA_{ict}^{ord} = M_{ict}^{ord} \times X_{ict}/D_{ict} + X_{ict} \quad (9)$$

where  $M_{ict}^{ord}$  denotes firm  $i$ 's imported intermediates under general trade, and  $X_{ict}$  and  $D_{ict}$  represent the firm's export revenue and domestic sales revenue, respectively. The ratio  $[X_{ict}/(D_{ict} + X_{ict})]$  captures the share of general trade imports directed toward export production. The total foreign value added embedded in firm  $i$ 's exports is thus:

$$FVA_{ict} = FVA_{ict}^{proc} + FVA_{ict}^{ord} = M_{ict}^{proc} + M_{ict}^{ord} \times X_{ict}/D_{ict} + X_{ict} \quad (10)$$

and the firm-level DVAR is obtained as:

$$DVAR_{ict} = 1 - FVA_{ict}/X_{ict} \quad (11)$$

This firm-level measurement framework avoids the aggregation bias inherent in macro input-output decomposition and captures the genuine heterogeneity in firms' GVC participation intensity arising from differences in trade regime composition, input sourcing structure, and market orientation.

Subsequently, the firm-level DVAR and FVAR are aggregated to the dual dimension of city-specific carbon-intensive industry using each firm's actual export value as the weighting factor. This weighting scheme ensures that firms with larger export volumes—which contribute more substantially to the city-industry's overall GVC embedding—receive pro-

portionally greater influence in the aggregated measure. Formally, the city-industry GVC participation index ( $GVCP_{ckt}$ ) for city  $c$  in carbon-intensive industry  $k$  at time  $t$  is constructed as the export-weighted average of firm-level FVARs:

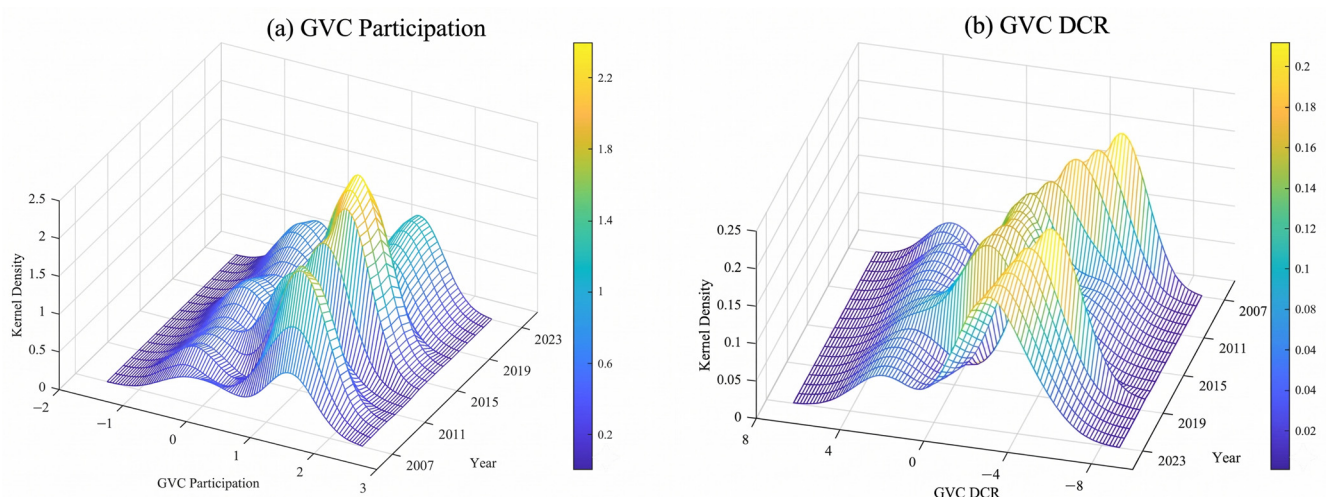
$$GVCP_{ckt} = \sum_{i \in ck} (FVAR_{ict} \times X_{ict}) / \sum_{i \in ck} X_{ict} \quad (12)$$

where  $\sum_{i \in ck} X_{ict}$  denotes the summation over all firms belonging to industry  $k$  in city  $c$ . The GVC DCR index ( $GVCS_{ckt}$ ) is derived as the export-weighted log ratio of DVAR to FVAR across firms within the same city-industry cell:

$$GVCS_{ckt} = \sum_{i \in ck} (\ln(DVAR_{ict}/FVAR_{ict}) \times X_{ict}) / \sum_{i \in ck} X_{ict} \quad (13)$$

A higher value of  $GVCS_{ckt}$  indicates that the city-industry occupies a relatively upstream position in the global value chain, contributing more domestic value added relative to foreign value added in its exports, whereas a lower value signals downstream dependence on imported intermediates.

This micro-founded measurement strategy offers three key advantages over the conventional macro MRIO decomposition. First, it eliminates the ecological fallacy arising from the uniform assignment of national-level indices to heterogeneous cities, thereby preserving authentic spatial variation in GVC embedding. Second, by exploiting the regulatory distinction between processing and general trade at the firm level, the proportional allocation method achieves a more accurate identification of the domestic and foreign content embedded in exports, an identification that is structurally impossible at the aggregate level. Third, the export-weighted aggregation from firms to the city-industry dimension ensures strict alignment between the explanatory and dependent variables at both the spatial and industrial hierarchical levels, thereby providing a clean and robust data foundation for causal identification in the subsequent double debiased machine learning estimation. Figure 2 shows that the distribution of GVC Participation exhibited a multi-peaked pattern with shifting peak positions, suggesting that GVC participation patterns and depth diverged over time. The distribution of GVC DCR showed dynamic changes, indicating that the GVC DCR of various cities was continuously evolving.



**Figure 2.** Kernel density distributions for GVC embedding.

### 3.2.3. Mechanism Variable

First, intermediate export quality (IEQ). Carbon-intensive industries occupy upstream positions in global production networks; the relevant quality-upgrading channel is therefore the intermediate product market. This study constructs a city-industry-year IEQ

index using micro-level customs transaction data from the China Foreign Trade Statistics Database, restricted to intermediate products under the Broad Economic Categories framework. Export quality is estimated via a structural demand model in which higher-quality products command higher unit values after controlling for price competition from alternative suppliers within the same destination market, with product–destination–time fixed effects absorbing common demand shocks. The aggregate IEQ is the revenue-share weighted average of estimated quality across all intermediate products exported by city in carbon-intensive industry.

Second, technology market activity (TMA). The technology environment enabling innovation depends not only on internal knowledge but also, more importantly, on external technology inputs and market-mediated knowledge exchange. This study uses a TMA index defined as the total value of technology contracts concluded in the city's technology market. Unlike patent-based measures that conflate the mechanism channel with the dependent variable, TMA captures genuine external inputs—the supply of, demand for, and institutional infrastructure facilitating technology transactions. The raw measure (total transaction value in RMB 10,000 per city-year) is log-transformed to ensure cross-city comparability, with a unit addition retaining zero-activity cities without selection bias.

Third, climate policy uncertainty (CPU). For carbon-intensive industries in GVC, the primary climate-related innovation driver is transition risk—regulatory pressures from international climate governance, carbon border adjustment, and decarbonization mandates—rather than physical risk. The city-level CPU index is constructed through a three-stage text-analysis pipeline applied to local policy documents and municipal regulatory gazettes. First, a keyword dictionary encompasses carbon governance, decarbonization mandates, international alignment, and regulatory implementation terms. Second, keyword occurrences per city-year are normalized by total document count. Third, each occurrence is weighted by co-occurrence of uncertainty-related terms. The final index captures regulatory pressure that compels anticipatory innovation.

Finally, environmental violation disclosure (EVD). The regulatory environment is shaped not by policy pronouncements but by substantive enforcement. The EVD index is constructed from objective administrative records obtained from the Ministry of Ecology and Environment's Environmental Violation and Penalty Disclosure System, supplemented by the IPE database. For each city-year, three indicators are collected: violation cases penalized, total penalty amount (in RMB 10,000), and production suspension days ordered. The composite index is the arithmetic mean of the three z-score normalized components—capturing detection, deterrence, and compliance pressure, respectively—each standardized by city-specific standard deviation. A higher EVD value indicates more stringent enforcement compelling innovation as a compliance strategy.

### 3.2.4. Control Variable

DDML effectively accommodates high-dimensional control variables through regularization techniques. Accordingly, based on existing literature [39] and data availability, this study selected six city-level variables and their quadratic terms as potential controls to enhance model fit and mitigate omitted-variable bias: economic development ( $\ln GDP$ ), financial development (*Finance*), government intervention (*GOV*), industrial structure (*Indus*), open-up (*Open*), and human capital (*HC*). The measurement methods of these control variables are detailed in Table A2.

### 3.3. Sample Selection and Descriptive Statistics

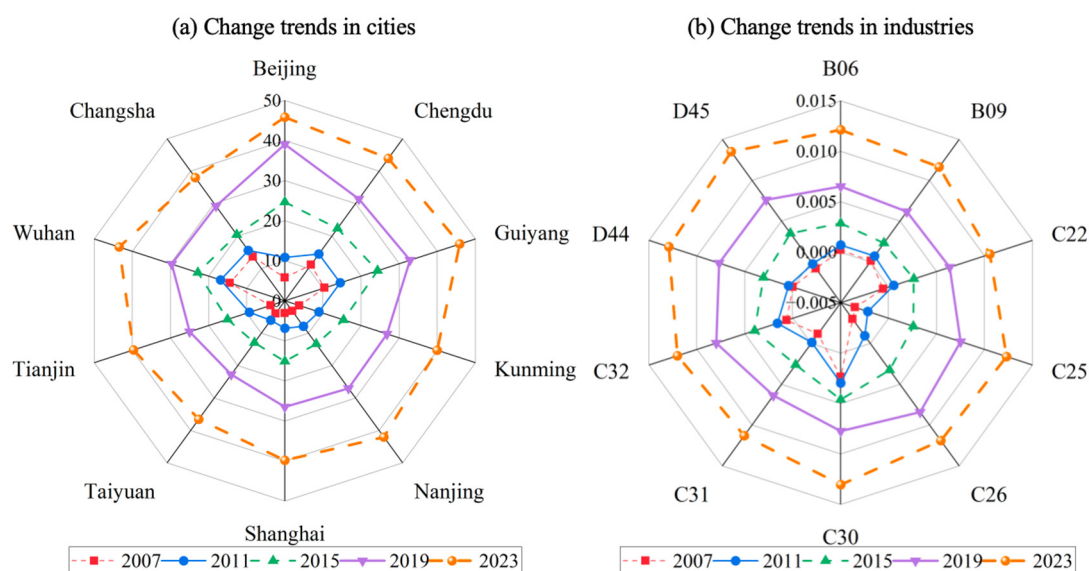
According to [40], ten carbon-intensive industries were identified based on China's National Economic Industry Classification (GB/T 4754-2017) [41], as shown in Table 1.

This study focuses on innovation in urban carbon-intensive industries from 2007 to 2023. Figure 3 showed that innovation output in carbon-intensive industries rose steadily across major cities and sectors during the sample period. Descriptive statistics for the main variables are reported in Table 2.

**Table 1.** Classification of carbon-intensive industries.

| Carbon-Intensive Industry                                           | Secondary Code | Primary Industry                                                 | Primary Code |
|---------------------------------------------------------------------|----------------|------------------------------------------------------------------|--------------|
| Coal mining and washing industry                                    | B06            | Mining industry                                                  | B            |
| Non-metallic mineral mining and processing industry                 | B09            | Mining industry                                                  | B            |
| Paper-making and paper products industry                            | C22            | Manufacturing industry                                           | C            |
| Petroleum, coal, and other fuel processing industry                 | C25            | Manufacturing industry                                           | C            |
| Chemical raw materials and chemical products manufacturing industry | C26            | Manufacturing industry                                           | C            |
| Non-metallic mineral products industry                              | C30            | Manufacturing industry                                           | C            |
| Black metal smelting and rolling processing industry                | C31            | Manufacturing industry                                           | C            |
| Non-ferrous metal smelting and rolling processing industry          | C32            | Manufacturing industry                                           | C            |
| Electricity, heat production and supply industry                    | D44            | Electricity, heat, gas, and water production and supply industry | D            |
| Gas production and supply industry                                  | D45            | Electricity, heat, gas, and water production and supply industry | D            |

Notes: The industrial classification in this study is based on China's National Economic Industry Classification (GB/T 4754-2017).



**Figure 3.** The changing trends of ICII averages in major cities and industries.

**Table 2.** The descriptive statistics of the main variables.

| Variable       | Obs.   | Mean   | Median | SD    | Min    | Max   |
|----------------|--------|--------|--------|-------|--------|-------|
| <i>ICII</i>    | 45,900 | 0.191  | 0.000  | 3.802 | −0.506 | 294.5 |
| <i>GVC-Par</i> | 45,900 | 0.000  | −0.239 | 1.000 | −1.501 | 2.523 |
| <i>GVC-DCR</i> | 45,900 | −2.074 | −2.461 | 3.480 | −8.874 | 6.708 |
| <i>LnGDP</i>   | 45,900 | 16.53  | 16.46  | 1.007 | 13.34  | 19.97 |
| <i>Indus</i>   | 45,900 | 45.94  | 46.30  | 11.16 | 11.59  | 90.97 |
| <i>GOV</i>     | 45,900 | 0.188  | 0.163  | 0.097 | 0.044  | 1.027 |
| <i>Finance</i> | 45,900 | 1.020  | 0.834  | 0.649 | 0.075  | 12.82 |
| <i>Open</i>    | 45,900 | 0.192  | 0.082  | 0.317 | 0.000  | 3.384 |
| <i>HC</i>      | 45,900 | 0.019  | 0.010  | 0.024 | 0.000  | 0.147 |
| <i>IEQ</i>     | 29,590 | 12.90  | 12.94  | 0.612 | 0.000  | 14.25 |
| <i>TMA</i>     | 45,900 | 4.224  | 4.248  | 1.912 | 0.000  | 9.872 |
| <i>CPU</i>     | 28,370 | 3.269  | 3.283  | 0.292 | −1.078 | 4.885 |
| <i>EVD</i>     | 43,800 | 0.000  | −0.100 | 1.000 | −2.761 | 6.362 |

## 4. Empirical Analysis

### 4.1. Impact of GVC Embedding on Innovation in Carbon-Intensive Industries

To examine the direct effect of GVC embedding on ICII, a DDML partial linear model was employed. Estimations were conducted using multiple algorithms, including Neural Network (NNT), Elastic Network (ELN), Lasso Regression (Lasso), and Ridge Regression (Ridge). A one-unit increase in GVC participation and DCR raised innovation output by 0.065–0.189 and 0.148–0.170 units, respectively (Table 3). These results provide empirical support for Hypothesis 1, indicating that GVC embedding promotes innovation-driven upgrading in carbon-intensive industries by mitigating path dependency through technological and informational channels.

**Table 3.** Benchmark regression results from the partial linear model.

| Variable       | Explanatory Var.: GVC Participation |                      |                      |                      | Explanatory Var.: GVC DCR |                      |                      |                      |
|----------------|-------------------------------------|----------------------|----------------------|----------------------|---------------------------|----------------------|----------------------|----------------------|
|                | NNT                                 | ELN                  | Lasso                | Ridge                | NNT                       | ELN                  | Lasso                | Ridge                |
| <i>GVC-Par</i> | 0.065 ***<br>(0.024)                | 0.188 ***<br>(0.069) | 0.189 ***<br>(0.072) | 0.185 ***<br>(0.058) |                           |                      |                      |                      |
| <i>GVC-DCR</i> |                                     |                      |                      |                      | 0.148 ***<br>(0.028)      | 0.168 ***<br>(0.040) | 0.170 ***<br>(0.040) | 0.170 ***<br>(0.060) |
| Cluster        | 2700                                | 2700                 | 2700                 | 2700                 | 2700                      | 2700                 | 2700                 | 2700                 |
| Linear         | YES                                 | YES                  | YES                  | YES                  | YES                       | YES                  | YES                  | YES                  |
| Quadratic      | YES                                 | YES                  | YES                  | YES                  | YES                       | YES                  | YES                  | YES                  |
| Year FE        | YES                                 | YES                  | YES                  | YES                  | YES                       | YES                  | YES                  | YES                  |
| City FE        | YES                                 | YES                  | YES                  | YES                  | YES                       | YES                  | YES                  | YES                  |
| Industry FE    | YES                                 | YES                  | YES                  | YES                  | YES                       | YES                  | YES                  | YES                  |
| Obs.           | 45,900                              | 45,900               | 45,900               | 45,900               | 45,900                    | 45,900               | 45,900               | 45,900               |

Notes: \*\*\* denotes significance levels of 1%. Values in parentheses represent cluster-robust standard errors at the urban carbon-intensive industry level. Linear and Quadratic refer to the linear and squared terms of the control variables, respectively.

Figures A1 and A2 illustrate the model fit and time-series forecasting performance of the four machine learning algorithms. As shown in Figure A1, the NNT algorithm achieved the highest goodness-of-fit. Figure A2 further confirms this advantage, with the 90% prediction interval of NNT noticeably narrower than those of the other three algorithms. To formally test these differences, Diebold–Mariano (DM) tests were conducted on the cross-fitted test-sample predictions (Table A3). The results reveal a performance hierarchy: NNT significantly outperforms ELN, Lasso, and Ridge at the 1% level for

GVC embedding. This hierarchy reflects the algorithms' differential capacity to handle nonlinearities and provides two grounds for selecting NNT: First, its statistically confirmed superiority demonstrates the ability to capture the complex nonlinear patterns of GVC embedding's impact on innovation; second, its narrower prediction intervals imply more robust and reliable estimates in high-dimensional covariate settings, providing a precise machine learning foundation for causal effect estimation.

#### 4.2. Endogeneity Test

To address potential reverse causality and omitted variable bias, this study constructs a Bartik instrumental variable (Bartik-IV) for 2SLS regression estimation, supplemented by the DDML-IV approach [42]. The shift component captures GVC import growth rates of corresponding carbon-intensive industries in high-income economies, driven by their own demand and regulatory conditions exogenous to Chinese city-level innovation. The share component is the innovation share of carbon-intensive industry in cities during the base period (2007), fixed before the sample and thus plausibly exogenous to subsequent innovation shocks.

Instrument validity rests on three conditions. For relevance, exogenous foreign import demand transmits through supply chains to Chinese exporters proportional to base-period industrial concentration; the Kleibergen–Paap rk Wald F statistics of GVC participation and positioning are 18.23 and 17.86, respectively, with both exceeding the Stock–Yogo 10% critical value of 16.38 (Table 4). For exogeneity, both components are determined prior to or outside the estimation framework. For the exclusion restriction, replacing the domestic shift with foreign GVC import growth eliminates the primary threat of co-occurring domestic policies. Although foreign demand shocks might affect innovation through price, spillover, or competition channels, these operate through trade relationships embedded in GVCs rather than independently. To empirically validate this, the Bartik-IV was decomposed into four region-specific instruments (United States, European Union, Japan–Korea, and other high-income economies), yielding three overidentifying restrictions. The Hansen J statistics of GVC participation and positioning are 2.14 and 1.87, respectively, with neither rejecting valid instruments.

**Table 4.** Empirical results of endogeneity tests.

| Variable         | Explanatory Var.: GVC Participation |                  | Explanatory Var.: GVC DCR |                     |
|------------------|-------------------------------------|------------------|---------------------------|---------------------|
|                  | 2SLS Regression                     | DDML             | 2SLS Regression           | DDML                |
| <i>Bartik-IV</i> | 0.032 ***<br>(0.002)                |                  | 0.068 ***<br>(0.005)      |                     |
| <i>GVC-Par</i>   |                                     | 1.475<br>(1.178) |                           | 0.052 **<br>(0.021) |
| <i>GVC-DCR</i>   |                                     |                  | 0.696<br>(0.556)          | 0.043 **<br>(0.021) |
| KP-WF            | 18.23<br>(16.38)                    |                  | 17.86<br>(16.38)          |                     |
| Hansen J         | 2.14<br>[0.543]                     |                  | 1.87<br>[0.599]           |                     |
| AR 95% CI        | [−0.83, 3.78]                       |                  | [−0.39, 1.79]             |                     |
| Cluster          | 2700                                | 2700             | 2700                      | 2700                |
| Linear           | YES                                 | YES              | YES                       | YES                 |
| Quadratic        | YES                                 | YES              | YES                       | YES                 |
| Year FE          | YES                                 | YES              | YES                       | YES                 |

Table 4. Cont.

| Variable    | Explanatory Var.: GVC Participation |        |        | Explanatory Var.: GVC DCR |        |        |
|-------------|-------------------------------------|--------|--------|---------------------------|--------|--------|
|             | 2SLS Regression                     |        | DDML   | 2SLS Regression           |        | DDML   |
| Industry FE | YES                                 | YES    | YES    | YES                       | YES    | YES    |
| Obs.        | 45,900                              | 45,900 | 45,900 | 45,900                    | 45,900 | 45,900 |

Notes: \*\* and \*\*\* denote significance at the 5% and 1% levels, respectively; values in parentheses represent the cluster robust standard errors at the urban carbon-intensive industry level; KP-WF represents Kleibergen–Paap rk Wald F statistics; Stock–Yogo 10% critical value is 16.38; brackets below the Hansen J test value represent the *p*-value; AR 95% c CI represents Anderson–Rubin 95% confidence interval; Linear and Quadratic indicate linear and quadratic terms of the control variables, respectively.

After instrumenting, the DDML-IV coefficients remain positive and significant: 0.052 for GVC participation and 0.043 for GVC DCR (Table 4). The 2SLS point estimates are larger but imprecise, with Anderson–Rubin 95% confidence intervals of  $[-0.83, 3.78]$  and  $[-0.39, 1.79]$  that encompass the DDML-IV estimates. This magnitude difference reflects two factors: 2SLS identifies the LATE for compliers—export-oriented city-industries with stronger absorptive capacity—while DDML-IV identifies a semiparametrically adjusted average effect, and linear 2SLS imposes constant treatment effects, whereas DDML-IV flexibly controls for high-dimensional confounders, yielding more efficient estimates. The wide 2SLS confidence intervals confirm that the two approaches are statistically consistent rather than contradictory.

#### 4.3. Robustness Test

##### 4.3.1. Alternative Estimation Method

To address potential biases arising from model specification, OLS estimation was employed for robustness tests. The results are reported in the first and fourth columns of Table 5. The promoting effect of GVC embedding on the innovation of urban carbon-intensive industries remains significant, confirming model robustness.

Table 5. Empirical results of the robustness tests.

| Variable       | Explanatory Var.: GVC Participation |                      |                      | Explanatory Var.: GVC DCR |                      |                      |
|----------------|-------------------------------------|----------------------|----------------------|---------------------------|----------------------|----------------------|
|                | OLS Estimation                      | Kfolds = 4           | Winsorization        | OLS Estimation            | Kfolds = 4           | Winsorization        |
| <i>GVC-Par</i> | 0.194 ***<br>(0.065)                | 0.082 ***<br>(0.015) | 0.912 ***<br>(0.014) |                           |                      |                      |
| <i>GVC-DCR</i> |                                     |                      |                      | 0.017 ***<br>(0.006)      | 0.151 ***<br>(0.011) | 0.162 ***<br>(0.003) |
| Cluster        | 2700                                | 2700                 | 2700                 | 2700                      | 2700                 | 2700                 |
| Linear         | YES                                 | YES                  | YES                  | YES                       | YES                  | YES                  |
| Quadratic      | YES                                 | YES                  | YES                  | YES                       | YES                  | YES                  |
| Year FE        | YES                                 | YES                  | YES                  | YES                       | YES                  | YES                  |
| City FE        | YES                                 | YES                  | YES                  | YES                       | YES                  | YES                  |
| Industry FE    | YES                                 | YES                  | YES                  | YES                       | YES                  | YES                  |
| Obs.           | 45,900                              | 45,900               | 45,900               | 45,900                    | 45,900               | 45,900               |

Notes: \*\*\* denotes significance at the 1% levels. The values in parentheses represent cluster-robust standard errors at the urban carbon-intensive industry level. Linear and Quadratic refer to the linear and quadratic terms of the control variables, respectively.

##### 4.3.2. Change Model Parameter

To further enhance data utilization efficiency, the sample split ratio was set to 4, and the estimation was repeated. The results are shown in the second and fifth columns of Table 5. After adjusting the sample split ratio, the industrial innovation effect of GVC embedding remains robust, reinforcing the reliability of the baseline regression.

#### 4.3.3. Treatment of Outliers

To minimize the impact of outliers on estimation results, a 1% Winsorization was applied to all variables. The results are shown in the third and sixth columns of Table 5, validating the conclusions of this study and the robustness of the baseline regression.

#### 4.4. Causal Mediation Analysis

To formally decompose the total effect (TE) of GVC embedding on the innovation of carbon-intensive industries into direct and indirect effects, this study adopts the causal mediation framework implemented within the DDML architecture. For each mediator  $M_k$  ( $k = IEQ, TMA, CPU, EVD$ ), the TE is decomposed as:

$$TE = ACME_k + ADE_k \quad (14)$$

where  $ACME_k = \hat{\alpha}_k \times \hat{\beta}_k$  represents the average causal mediation effect and captures the indirect effect transmitted through  $M_k$ ,  $ADE_k = TE_k - ACME_k$  represents the average direct effect and measures the residual direct impact, the first-stage coefficient  $\hat{\alpha}_k$  and the second-stage coefficient  $\hat{\beta}_k$  are estimated via cross-fitted orthogonalization with neural network algorithm ( $K = 5$  folds), and inference for ACME uses the multiplier bootstrap ( $B = 1000$ ). Identification rests on the sequential ignorability assumption, strengthened by DDML's flexible control for high-dimensional confounders.

##### 4.4.1. Intermediate Export Quality

To examine the indirect effect of GVC embedding on the innovation of carbon-intensive industries via the urban export environment, the urban intermediate export quality (IEQ) was introduced as the proxy variable. The results are shown in Table 6. The estimation results reveal that GVC embedding significantly enhances the intermediate export quality of carbon-intensive industries, with the indirect effect (ACME) of 0.011 for GVC participation and 0.024 for GVC DCR. From the perspective of the proportion mediated, IEQ conveyed 16.9% of the total effect of GVC participation and 16.2% of the total effect of GVC DCR, respectively. These findings indicate that both the depth and the position of GVC integration serve as effective conduits for quality upgrading in upstream export activities.

**Table 6.** Empirical results of the causal mediation tests.

| Variable                                | $\alpha$              | $\beta$              | ACME                 | ADE                  | PM (%) |
|-----------------------------------------|-----------------------|----------------------|----------------------|----------------------|--------|
| Panel A: GVC Participation (TE = 0.065) |                       |                      |                      |                      |        |
| IEQ                                     | 0.132 ***<br>(0.015)  | 0.083 ***<br>(0.021) | 0.011 **<br>(0.005)  | 0.054 ***<br>(0.011) | 16.9   |
| TMA                                     | 0.534 ***<br>(0.011)  | 0.046 ***<br>(0.013) | 0.025 ***<br>(0.007) | 0.040 ***<br>(0.010) | 38.5   |
| CPU                                     | 0.159 ***<br>(0.001)  | 0.077 **<br>(0.032)  | 0.012 **<br>(0.005)  | 0.053 ***<br>(0.011) | 18.5   |
| EVD                                     | −0.228 ***<br>(0.007) | 0.033 *<br>(0.018)   | −0.008 *<br>(0.004)  | 0.073 ***<br>(0.014) | −12.3  |
| Joint                                   |                       |                      | 0.040 ***<br>(0.010) | 0.025 ***<br>(0.009) | 61.5   |
| Panel B: GVC DCR (TE = 0.148)           |                       |                      |                      |                      |        |
| IEQ                                     | 0.250 ***<br>(0.005)  | 0.094 ***<br>(0.024) | 0.024 ***<br>(0.007) | 0.124 ***<br>(0.018) | 16.2   |
| TMA                                     | 0.092 ***<br>(0.004)  | 0.053 ***<br>(0.015) | 0.005 **<br>(0.002)  | 0.143 ***<br>(0.021) | 3.4    |

Table 6. Cont.

| Variable | $\alpha$              | $\beta$             | ACME                 | ADE                  | PM (%) |
|----------|-----------------------|---------------------|----------------------|----------------------|--------|
| CPU      | −0.013 ***<br>(0.002) | 0.066 **<br>(0.028) | −0.001<br>(0.001)    | 0.149 ***<br>(0.022) | −0.7   |
| EVD      | 0.015 ***<br>(0.004)  | 0.039 *<br>(0.021)  | 0.001<br>(0.001)     | 0.147 ***<br>(0.022) | 0.7    |
| Joint    |                       |                     | 0.029 ***<br>(0.008) | 0.119 ***<br>(0.015) | 19.6   |

Notes: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively; The values in parentheses represent the cluster robust standard errors at the urban carbon-intensive industry; TE values are from Table 3 (NNT algorithm); PM = (ACME/TE) × 100%; Joint ACME tests H: all ACME = 0, simultaneously; Benjamini–Hochberg adjusted *p*-values are shown in Table A4.

The economic logic underlying this result is rooted in the structural position of carbon-intensive industries within global production networks. As upstream suppliers of raw materials, energy, and intermediate inputs, these industries face quality-upgrading pressure not from terminal consumers, but from downstream buyers who impose increasingly stringent technical and environmental specifications on intermediate products. This pattern is particularly evident when domestic firms participate in global supply chains—particularly through processing trade of intermediate goods. The stronger effect of GVC DCR further suggests that moving toward upstream specialization enhances firms’ capacity to produce differentiated, high-quality intermediate inputs, rather than competing solely on price in commoditized markets. This finding carries important policy implications: for carbon-intensive industries, the critical export channel for innovation stimulus lies in intermediate product upgrading, not in expanding the volume of finished goods exports. Policies that facilitate access to high-end intermediate trade segments—such as quality certification programs and alignment with international product standards—may be more effective than traditional export promotion measures.

#### 4.4.2. Technology Market Activity

Technology market activity (TMA) was used as the proxy variable to assess the effect of GVC embedding on the urban technological environment. The results are shown in Table 6. GVC embedding exerts a positive effect on the urban technological environment, though with notable heterogeneity across embedding modes. A one-unit increase in GVC participation raises technology market activity by 0.534 units, whereas the corresponding effect of GVC DCR is substantially smaller, at 0.092. The indirect effect (ACME) is 0.025 for GVC participation (PM is 38.5%) and 0.005 for GVC DCR (PM is 3.4%). This asymmetry reveals fundamentally different pathways through which the two dimensions of GVC embedding shape the technology environment.

The large coefficient on GVC participation reflects the scale and immediacy of technology market activation triggered by deep integration into global production networks. When carbon-intensive industries increase their participation in international intermediate goods trade, they generate direct demand for external technology acquisition—importing advanced process technologies, licensing emission-reduction solutions, and contracting R&D services—to meet the technical requirements imposed by downstream global buyers. This demand-side stimulus is amplified by the supply-side response: GVC participation attracts foreign technology providers, R&D centers, and innovation intermediaries to the local market, enriching the technology transaction ecosystem. In contrast, the modest effect of GVC DCR suggests that upstream capability accumulation operates through a different, more gradual channel. Firms in higher GVC positions possess stronger absorptive capacity and internal R&D capabilities, which reduces their reliance on external technology markets but enhances their ability to selectively identify and integrate externally available

knowledge. The net effect on technology market transactions is therefore positive but attenuated. This finding underscores a crucial distinction: GVC participation activates the technology market primarily through demand-pull mechanisms, while GVC DCR contributes through supply-side capability deepening—both channels ultimately facilitate innovation in carbon-intensive industries, but through temporally distinct pathways that warrant differentiated policy support.

#### 4.4.3. Climate Policy Uncertainty

To examine the indirect effect of GVC embedding through the urban climate environment, urban climate policy uncertainty (CPU) was used as the proxy variable. The results are shown in Table 6. The effects of GVC embedding on CPU exhibit a striking asymmetry: GVC participation raises climate policy uncertainty, while GVC DCR reduces it. Crucially, the second-stage coefficient  $\beta$  is positive and significant in both panels, indicating that higher CPU is associated with greater innovation output. The indirect effect (ACME) is 0.012 for GVC participation and  $-0.001$  for GVC DCR.

The positive  $\beta$  coefficient warrants careful theoretical justification, as the innovation economics literature advances two competing hypotheses regarding the uncertainty–innovation nexus. Real options theory posits that uncertainty constrains R&D investment because firms defer irreversible investments until the regulatory environment becomes clearer—the option effect. Strategic growth option theory, by contrast, argues that under competitive conditions, uncertainty can encourage early innovation investment because preemptive action secures strategic advantages—the precautionary innovation effect. Three context-specific factors tip the balance toward the latter for carbon-intensive industries embedded in GVCs. First, unlike general policy uncertainty, climate policy has a clear directional bias—toward stricter regulation—so the option value of waiting is inherently low; firms recognize that delayed action will only increase future compliance costs. Second, GVC-induced competitive pressure—carbon border adjustment mechanisms, supply chain decarbonization mandates, and international buyer requirements—means the cost of inaction substantially exceeds the sunk cost of premature innovation. Third, green innovation in carbon-intensive industries typically involves incremental process improvements and technology licensing rather than large-scale irreversible capital expenditure, which further attenuates the option effect.

#### 4.4.4. Environmental Violation Disclosure

To examine the indirect effect of GVC embedding through the urban regulatory environment, this study used environmental violation disclosure (EVD) as the proxy variable. The results are shown in Table 6. GVC embedding had asymmetric effects on the urban regulatory environment depending on the embedding mode. A one-unit increase in GVC participation reduces EVD by 0.228 units, whereas a one-unit increase in GVC DCR increases EVD by 0.015 units. The indirect effect (ACME) is  $-0.008$  for GVC participation and 0.001 for GVC DCR. This asymmetry illuminates the dual institutional logic of GVC integration.

The negative effect of GVC participation on EVD reveals a regulatory race-to-the-bottom dynamic. Cities seeking to attract and retain globally integrated carbon-intensive industries—particularly those engaged in low-value-added processing trade—may strategically weaken environmental enforcement to maintain their competitive position as investment destinations. The logic is straightforward: stricter environmental enforcement raises compliance costs, which can prompt mobile capital to relocate to jurisdictions with laxer regulation. In this scenario, deeper GVC participation paradoxically undermines the very regulatory standards that international governance frameworks aim to promote, creating a

regulatory externality whereby the benefits of GVC integration are captured locally while the environmental costs are partially externalized.

Conversely, the positive effect of GVC DCR on EVD reflects a regulatory alignment mechanism. Cities occupying higher-value positions in global value chains tend to enforce environmental regulations more rigorously because their competitive advantage derives not from cost minimization through regulatory arbitrage, but from quality differentiation and compliance with international standards. Firms in these cities must demonstrate credible environmental performance to maintain their market access and reputational capital in high-end GVC segments, which incentivizes local governments to strengthen enforcement and transparency. The EVD index, constructed from objective violation and penalty records rather than rhetorical policy statements, captures this substantive divergence in regulatory enforcement. Taken together, these findings suggest that the regulatory dimension of GVC embedding operates as a double-edged sword: while participation intensity may erode enforcement standards, upward positioning within the value chain reinforces regulatory convergence with international norms. Policy interventions must therefore address the structural incentives that drive regulatory competition among participating cities, while simultaneously leveraging the compliance pressure inherent in high-value GVC segments to strengthen de facto environmental enforcement.

#### 4.5. Heterogeneity Analysis

##### 4.5.1. Industrial Characteristics

The innovation effects of GVC embedding vary significantly across carbon-intensive industries. To explore this heterogeneity, the study differentiated among mining, manufacturing, and electricity, heat, gas, and water (EHGW) industries. As shown in Table 7, both GVC participation and positioning significantly promoted innovation in mining industries. In EHGW industries, GVC participation fostered innovation, but GVC DCR suppressed it. In manufacturing, GVC participation was insignificant and positioning significantly reduced innovation. Chow tests confirm that the negative positioning effects in manufacturing and EHGW differ significantly from the positive mining effect, substantiating that the cross-industry heterogeneity is statistically robust rather than an artifact of coefficient magnitude comparison. For GVC participation, manufacturing and EHGW differ significantly, while the mining–manufacturing and mining–EHGW participation differences are not significant, indicating that heterogeneity in the participation channel is concentrated between the manufacturing and utility sectors.

**Table 7.** Empirical results of the heterogeneity tests.

| Panel A: Industrial characteristics        | GVC Participation |         | GVC DCR   |         | Obs.   |
|--------------------------------------------|-------------------|---------|-----------|---------|--------|
| Mining                                     | 0.098 ***         | (0.035) | 0.296 *** | (0.048) | 9180   |
| Manufacturing                              | 0.028             | (0.026) | −0.067 ** | (0.031) | 27,540 |
| EHGW                                       | 0.142 ***         | (0.041) | −0.089 ** | (0.036) | 9180   |
| Chow test values: Mining and Manufacturing | 2.58              | [0.108] | 40.36 *** | [0.000] |        |
| Chow test values: Mining and EHGW          | 0.67              | [0.414] | 41.17 *** | [0.000] |        |
| Chow test values: Manufacturing and EHGW   | 5.51 **           | [0.019] | 0.21      | [0.647] |        |
| Panel B: Urban characteristics             | GVC Participation |         | GVC DCR   |         | Obs.   |
| Mature                                     | 0.085 ***         | (0.030) | 0.193 *** | (0.038) | 6460   |
| Growing                                    | 0.022             | (0.032) | 0.041     | (0.044) | 3060   |
| Recessionary                               | −0.041            | (0.036) | −0.072    | (0.048) | 4080   |
| Regenerative                               | −0.028            | (0.033) | −0.063 *  | (0.034) | 550    |

Table 7. *Cont.*

|                                                 |           |         |           |         |        |
|-------------------------------------------------|-----------|---------|-----------|---------|--------|
| Chow test values: Mature and Growing            | 2.06      | [0.151] | 6.83 ***  | [0.009] |        |
| Chow test values: Mature and Recessionary       | 7.23 ***  | [0.007] | 18.74 *** | [0.000] |        |
| Chow test values: Mature and Regenerative       | 6.42 **   | [0.011] | 25.21 *** | [0.000] |        |
| Chow test values: Growing and Recessionary      | 1.71      | [0.191] | 3.01 *    | [0.083] |        |
| Chow test values: Growing and Regenerative      | 1.18      | [0.277] | 3.50 *    | [0.061] |        |
| Chow test values: Recessionary and Regenerative | 0.07      | [0.786] | 0.02      | [0.879] |        |
| Baseline regression coefficients (full sample)  | 0.065 *** | (0.024) | 0.148 *** | (0.028) | 45,900 |

Notes: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively; The values in parentheses represent the cluster robust standard errors at the urban carbon-intensive industry; baseline regression coefficients are from Table 3 (NNT algorithm); Chow test *p*-values are in brackets; Chow test F-statistics are Wald tests for coefficient equality; Benjamini–Hochberg adjusted *p*-values are shown in Table A4.

This divergence is driven by industry-specific absorptive capacity. In manufacturing, higher GVC DCR often reflects import substitution through vertical integration or domestic sourcing rather than genuine technological upgrading. When firms reduce reliance on imported intermediates without commensurate R&D investment, they sever technology spillover channels—learning-by-doing, reverse engineering, and quality benchmarking, creating a positioning paradox: statistical improvement in GVC DCR accompanied by innovation stagnation. In EHGW, innovation depends heavily on importing advanced turnkey technologies; higher GVC DCR implies reduced import dependence, which reverses the technology spillover mechanism. Mining, by contrast, benefits from stronger technology integration capacity and resource endowments, enabling firms to translate upstream positioning into innovation gains. These findings indicate that GVC DCR promotes innovation only when supported by adequate absorptive capacity—conditions met in mining but not yet in manufacturing and EHGW.

#### 4.5.2. Urban Characteristics

Resource-based cities, defined as those reliant on natural resource extraction and primary processing, face challenges such as resource depletion, monolithic industrial structures, and path dependence during industrial transition. These cities were classified into four developmental stages: growing, mature, recessionary, and regenerative, to assess how GVC embedding influences innovation across carbon-intensive industries. As shown in Table 7, both GVC participation and positioning significantly enhanced innovation in mature cities, while the effects were insignificant or negative in other stages. Chow tests confirm significant structural breaks between mature and non-mature cities, particularly for GVC DCR and participation. Among non-mature cities, pairwise differences are generally insignificant, with only marginal positioning differences between growing and recessionary/regenerative cities, confirming that the mature-city advantage is the primary axis of heterogeneity rather than a gradient across all developmental stages.

Mature cities possess established industrial foundations, robust fiscal capacity, and advanced infrastructure that enable effective absorption of GVC knowledge spillovers. Growing cities prioritize resource exploitation but lack mature innovation systems, limiting their capacity to translate GVC links into innovation. Recessionary cities face financial constraints from resource depletion, while regenerative cities bear short-term disruption costs from abandoning established GVC pathways. The marginal positioning differences between growing and recessionary/regenerative cities suggest that growing cities retain a weak positive positioning channel, whereas cities in later transitional stages experience positioning reversals as resource-based GVC pathways are dismantled. These findings underscore that the innovation benefits of GVC embedding are contingent on urban developmental readiness: for cities lacking such readiness, policy should prioritize building absorptive infrastructure before deepening GVC integration.

#### 4.6. Further Discussion

To explore the heterogeneous effects of GVC participation modes, this study distinguished between forward and backward GVC participation and examined their heterogeneous effects on innovation in carbon-intensive industries. As shown in Table 8, the results reveal a significant asymmetry. Backward participation promoted innovation, whereas forward participation tended to suppress it. This asymmetry arises from differences in industrial roles, technology spillovers, and upgrading pressures associated with each mode. Forward participation positions domestic industries as suppliers of raw materials or intermediate goods, reinforcing comparative advantage traps based on resource endowments. Firms locked into low-end supply segments face cost-driven competition rather than innovation incentives, weakening motivation for green or value-added innovation and potentially entrenching technological inertia. Backward participation, by importing high-end intermediates, equipment, or technologies, facilitates direct technology spillovers and learning-by-doing. To absorb advanced inputs, domestic carbon-intensive industries engage in adaptive innovation and technological upgrading, transforming external pressure into a driver of innovation.

**Table 8.** The impact of different GVC participation modes on ICII.

| Variable            | GVC Forward Participation | GVC Backward Participation |
|---------------------|---------------------------|----------------------------|
| <i>GVC-Forward</i>  | −0.695 ***<br>(0.060)     |                            |
| <i>GVC-Backward</i> |                           | 0.311 ***<br>(0.035)       |
| Cluster             | 2700                      | 2700                       |
| Linear              | YES                       | YES                        |
| Quadratic           | YES                       | YES                        |
| Year FE             | YES                       | YES                        |
| City FE             | YES                       | YES                        |
| Industry FE         | YES                       | YES                        |
| Obs.                | 45,900                    | 45,900                     |

Notes: \*\*\* denotes significance at the 1% levels; values in parentheses represent cluster-robust standard errors at the urban carbon-intensive industry level; Linear and Quadratic indicate the linear terms and quadratic terms of the control variables, respectively; the DDML algorithm refers to the neural network; Benjamini–Hochberg adjusted *p*-values are shown in Table A4.

## 5. Research Conclusions and Policy Implications

### 5.1. Research Conclusions

With the deep restructuring of GVCs, the rapidly evolving external environment, and the urgent need for carbon emission governance, understanding the upgrading and innovation paths of carbon-intensive industries is critical for enhancing industrial competitiveness and promoting sustainable development. Using panel data covering 10 carbon-intensive industries in 270 Chinese cities from 2007 to 2023, this study integrated GVC embedding, the urban external environment, and carbon-intensive industry innovation into a unified framework and examined their complex interactions from both theoretical and empirical perspectives. Empirical results showed that GVC embedding directly promoted innovation in urban carbon-intensive industries through information amplification and innovation network optimization. Across multiple machine learning algorithms, each unit increase in GVC participation and GVC DCR raised innovation output by 0.065–0.189 and 0.148–0.170 units, respectively. These effects remained robust after endogeneity and robustness tests using *Bartik-IV*. Mechanism analyses indicated that GVC embedding optimized the innovation environment through four dimensions: upgrading intermediate export quality, stimulating technology market activity, internalizing climate policy uncertainty,

and aligning environmental violation disclosure. However, this effect was asymmetric due to the constraints of international production activities. Heterogeneity analyses revealed that the innovation effect of GVC embedding varied significantly across industries and cities. Innovation output was enhanced in the mining industry and mature resource-based cities but weakened or reversed in the sectors of manufacturing and EHGW and in growing, recessionary, and regenerative resource-based cities. The analysis of participation modes showed that deep forward GVC participation trapped industries in comparative lock-ins, inhibiting innovation, whereas backward participation facilitated learning-by-doing, boosting innovation capabilities.

## 5.2. Policy Implications

This study demonstrates that GVC embedding promotes innovation in carbon-intensive industries through multi-dimensional environmental reconfiguration, yet the effects are fundamentally conditioned by embedding modes, industrial characteristics, and urban developmental stages. These findings yield a governance framework that reconciles deeper global economic integration with carbon neutrality objectives, tailored to the structural specificities of carbon-intensive sectors. Several policy implications are derived:

First, differentiate GVC participation modes to harness backward linkages while preventing forward-linkage lock-in. Developing economies should incentivize backward participation—importing advanced intermediates and processing technologies—through tariff exemptions on green process equipment, accelerated depreciation for low-carbon machinery, and preferential credit lines for high-value-added intermediate imports. Concurrently, guardrails on pure forward participation are essential: value-added processing requirements before export licensing, carbon-intensity ceilings on raw mineral exports, and export quality thresholds that discourage low-end resource extraction. Aligning national product standards with international carbon accounting frameworks and establishing product-level embodied carbon databases further convert compliance pressure into an upgrading driver, ensuring that backward integration deepens rather than dilutes domestic innovation capacity.

Secondly, implement sector-specific mitigation for industries vulnerable to positioning-induced innovation stagnation. For manufacturing, mandating R&D matching ratios—requiring import-substituting firms to reinvest a share of cost savings in process innovation—coupled with phased emission standards creates regulated demand for green technology adoption. For energy-intensive heavy industries dependent on imported turnkey technologies, maintaining strategic technology import programs with mandatory local adaptation requirements (indigenous R&D matching funds, utility-scale demonstration projects, and licensing-based transfer conditions within defined timeframes) preserves learning-by-doing and reverse engineering channels during domestic capability building. Strengthening technology trading platforms, intellectual property protection for green patents, and tax incentives for technology contract transactions further amplifies the technology market activity channel, ensuring that positioning upgrading translates into innovation rather than stagnation.

Thirdly, adopt stage-contingent strategies that prioritize absorptive capacity before GVC deepening. Growing resource-dependent cities should first build innovation infrastructure: vocational training programs for green skills, regional technology extension services, and innovation incubation funds that lower the threshold for adaptive technology adoption. Recessionary cities, constrained by fiscal depletion, require targeted green transition funds earmarked for industrial diversification, worker retraining, and environmental remediation of abandoned extraction sites. Regenerative cities bearing short-term disruption costs from restructuring need transition support: industrial site redevelopment

incentives, new-industry incubation zones, and bridge financing during the transition period. Across all stages, enhancing regulatory predictability through long-term carbon pricing roadmaps, transparent emission standard trajectories, and mandatory corporate carbon disclosure with third-party verification converts climate policy uncertainty and environmental enforcement from investment deterrents into precautionary innovation drivers, completing the institutional reconfiguration needed at each urban development stage.

### 5.3. Research Limitations and Prospects

Despite its contributions, this study has limitations. First, the four mediating variables may be endogenous to unobserved determinants of innovation output. Although the DDML framework partially mitigates omitted-variable bias through high-dimensional controls and cross-fitting, it does not fully resolve mediator endogeneity: the estimated mediation effects should be interpreted as associational rather than strictly causal. Future research should construct valid instruments for each mediator and conduct formal exogeneity tests within a full causal mediation framework. Second, the current empirical model employs a linear specification that considers only additive effects, without modeling nonlinearities, interactions between mechanisms, or threshold effects. Future research could incorporate interaction terms between mechanisms into the model or adopt nonparametric/semiparametric estimation methods that allow for nonlinear interactions.

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## Appendix A

**Table A1.** The specific settings of the DDML framework and the NNT algorithm.

| Specification                                     | Setting                     | Detail and Justification                                                                                              |
|---------------------------------------------------|-----------------------------|-----------------------------------------------------------------------------------------------------------------------|
| Double debiased machine learning (DDML) framework |                             |                                                                                                                       |
| Empirical model                                   | Partial linear model        | Preserves linear interpretability of GVC variables while flexibly controlling for high-dimensional confounders.       |
| Orthogonality                                     | Neyman orthogonal moment    | Eliminates regularization bias from ML estimation of nuisance functions.                                              |
| Cross-fitting                                     | K = 5 folds                 | Sample randomly split into 5 equal parts; each fold serves as main sample once, with the remaining 4 as auxiliary.    |
| Nuisance functions                                | $\hat{A}_x$ and $\hat{D}_x$ | Conditional expectations $E[Y X]$ and $E[D X]$ estimated via NNT on auxiliary folds; residuals computed on main fold. |

Table A1. Cont.

| Specification                     | Setting                                         | Detail and Justification                                                                                         |
|-----------------------------------|-------------------------------------------------|------------------------------------------------------------------------------------------------------------------|
| Final estimator                   | OLS on residuals                                | $\hat{\theta} = (\sum \tilde{D}^2)^{-1} \sum \tilde{D} \tilde{y}$ ; asymptotically normal and root-n consistent. |
| Neural network (NNT) architecture |                                                 |                                                                                                                  |
| Hidden layers                     | 3                                               | Balances capacity vs. overfitting for 45,900 observations.                                                       |
| Neurons per layer                 | 64, 32, 16                                      | Decreasing architecture captures hierarchical feature representations.                                           |
| Activation function               | ReLU                                            | Standard for regression tasks; mitigates vanishing gradient.                                                     |
| Dropout rate                      | 0.15                                            | Applied to each hidden layer; prevents co-adaptation.                                                            |
| Optimizer                         | Adam ( $\beta_1 = 0.9$ ; $\beta_2 = 0.999$ )    | Adaptive learning rates for stable convergence.                                                                  |
| Learning rate                     | 0.001 (with decay)                              | Initial rate halved every 100 epochs; ensures fine-tuning in later stages.                                       |
| Batch size                        | 256                                             | Balances gradient stability and computational efficiency.                                                        |
| Epochs                            | 300 (early stopping)                            | Training halted if validation loss does not improve for 20 consecutive epochs.                                   |
| Loss function                     | MSE                                             | Consistent with the DDML objective of minimizing prediction error.                                               |
| Weight initialization             | He normal                                       | Optimized for ReLU activation.                                                                                   |
| Hyperparameter Selection          |                                                 |                                                                                                                  |
| Validation method                 | 5-fold internal CV                              | Within each auxiliary fold, an inner 5-fold CV selects optimal hyperparameters.                                  |
| Selection criterion               | Minimum validation MSE                          | Hyperparameters chosen to minimize out-of-sample prediction error.                                               |
| Tuned parameters                  | Layer width, dropout, learning rate, batch size | Grid search over candidate sets; final values reported above.                                                    |
| Random seed                       | 42 (replication seed)                           | Results robust to alternative seeds (123, 456, 789); coefficient variation < 5%.                                 |
| Sensitivity Checks                |                                                 |                                                                                                                  |
| Alternative K                     | K = 3, 7, 10                                    | Point estimates stable: $\hat{\theta}$ variation < 4% across K values.                                           |
| Alternative algorithms            | ELN, Lasso, Ridge                               | DM tests confirm NNT superiority (Table A3); DDML estimates remain qualitatively identical across algorithms.    |
| Median splitting                  | 5-fold median splitting                         | Results robust to median-based splitting (vs. mean-based); addresses potential outlier sensitivity.              |

Table A2. Definitions and measurements of the main variables.

| Variable | Definition                                | Measurement                           | Source                                 |
|----------|-------------------------------------------|---------------------------------------|----------------------------------------|
| ICII     | Innovation in carbon-intensive industries | Calculated by city-industry index     | The State Intellectual Property Office |
| GVC-Par  | GVC participation                         | Calculated by GVC participation index | China's customs database               |
| GVC-Pos  | GVC position                              | Calculated by GVC position index      | China's customs database               |

Table A2. Cont.

| Variable       | Definition              | Measurement                                                                                            | Source                                                                        |
|----------------|-------------------------|--------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| <i>LnGDP</i>   | Economic development    | The logarithm of urban GDP                                                                             | China Urban Statistical Yearbook;<br>The China Research Data Service Platform |
| <i>Finance</i> | Financial development   | The proportion of the balance of various loans of financial institutions at the end of the year to GDP |                                                                               |
| <i>GOV</i>     | Government intervention | The proportion of local fiscal general budgetary expenditure to GDP                                    |                                                                               |
| <i>Indus</i>   | Industrial structure    | The proportion of the added value of the secondary industry in GDP                                     |                                                                               |
| <i>Open</i>    | Open-up                 | The proportion of the total volume of imports and exports to GDP                                       |                                                                               |
| <i>HC</i>      | Human capital           | The proportion of the number of college students in the local registered population                    |                                                                               |

Table A3. Diebold–Mariano tests for pairwise algorithm comparison.

| Comparison      | GVC Participation |                 | GVC DCR      |                 |
|-----------------|-------------------|-----------------|--------------|-----------------|
|                 | DM Statistic      | <i>p</i> -Value | DM Statistic | <i>p</i> -Value |
| NNT and ELN     | −3.47 ***         | 0.001           | −3.21 ***    | 0.001           |
| NNT and Lasso   | −4.15 ***         | <0.001          | −3.95 ***    | <0.001          |
| NNT and Ridge   | −3.89 ***         | <0.001          | −3.68 ***    | <0.001          |
| ELN and Lasso   | 2.14 **           | 0.032           | 1.98 **      | 0.048           |
| ELN and Ridge   | −1.87 *           | 0.061           | −1.69 *      | 0.091           |
| Lasso and Ridge | −0.72             | 0.472           | −0.58        | 0.562           |

Notes: The Diebold–Mariano test compares pairwise forecast accuracy based on MSE loss differentials on cross-fitted test-sample predictions ( $K = 5$  folds,  $n = 45,900$ ); negative DM statistics indicate that the first-named algorithm has lower prediction error; \*\*\*, \*\*, and \* denote significance at the 1%, 5%, and 10% levels, respectively; null hypothesis is equal forecast accuracy; critical values are from the standard normal distribution.

Machine Learning Model Fitting Results

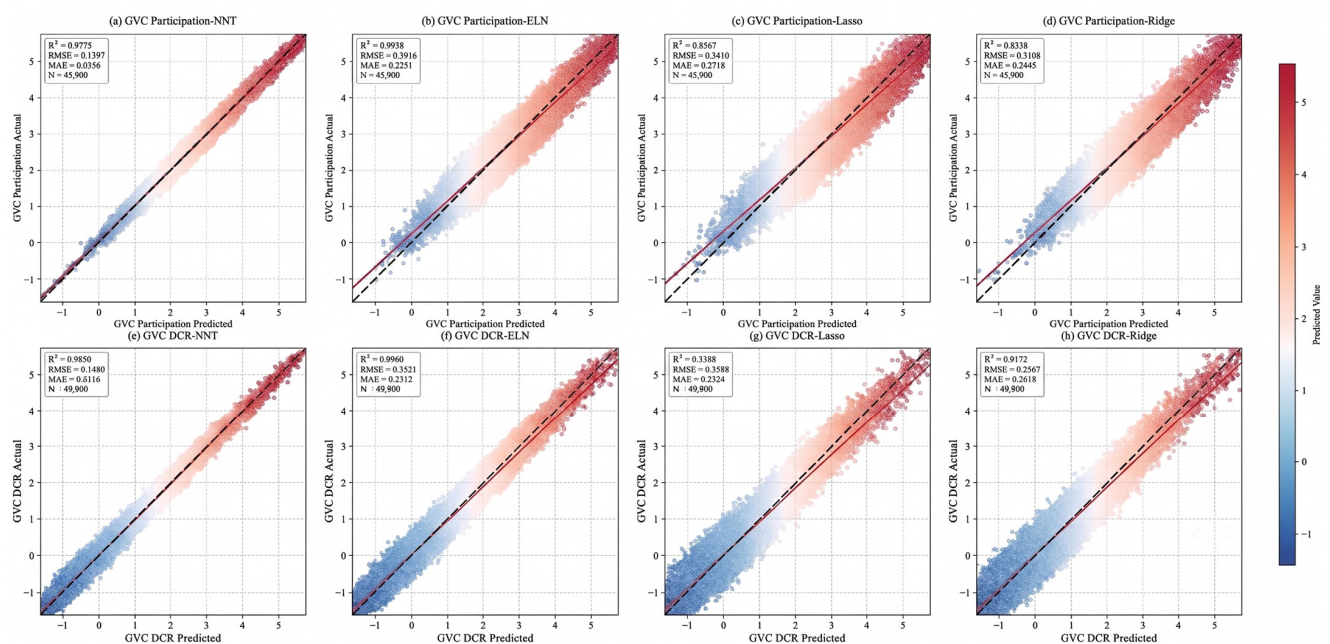
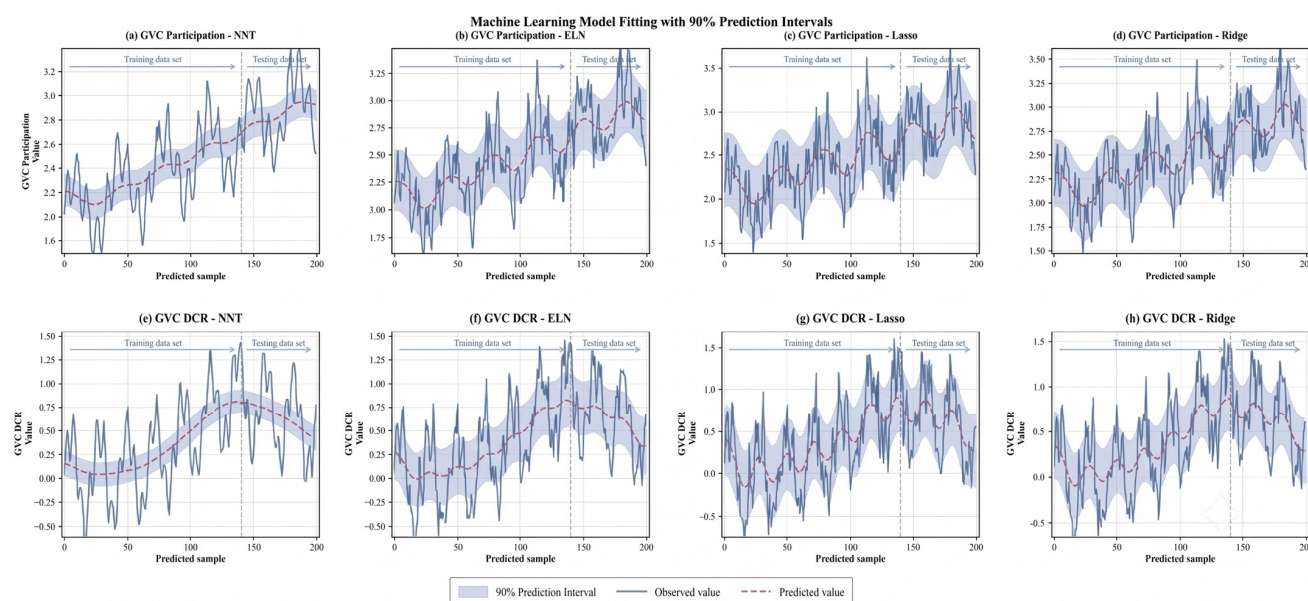


Figure A1. Model fitting renderings of various machine learning algorithms.



**Figure A2.** Model time series fitting renderings of various machine learning algorithms.

**Table A4.** Benjamini–Hochberg correction summary for all hypothesis families.

| Family                   | Test                         | Coefficient | Raw- <i>p</i> | BH- <i>q</i> | FDR < 0.1 |
|--------------------------|------------------------------|-------------|---------------|--------------|-----------|
| Table 6 ( <i>m</i> = 8)  | IEQ–GVC Participation        | 0.011 **    | 0.028         | 0.045        | Yes       |
|                          | TMA–GVC Participation        | 0.025 ***   | 0.001         | 0.004        | Yes       |
|                          | CPU–GVC Participation        | 0.012 **    | 0.016         | 0.032        | Yes       |
|                          | EVD–GVC Participation        | −0.008 *    | 0.046         | 0.061        | Yes       |
|                          | IEQ–GVC DCR                  | 0.024 ***   | 0.001         | 0.004        | Yes       |
|                          | TMA–GVC DCR                  | 0.005 **    | 0.012         | 0.032        | Yes       |
|                          | CPU–GVC DCR                  | −0.001      | 0.317         | 0.317        | No        |
|                          | EVD–GVC DCR                  | 0.001       | 0.317         | 0.317        | No        |
| Table 7 ( <i>m</i> = 14) | Mining–GVC Participation     | 0.098 ***   | 0.005         | 0.018        | Yes       |
|                          | Mining–GVC DCR               | 0.296 ***   | <0.001        | <0.001       | Yes       |
|                          | Manuf.–GVC Participation     | 0.028       | 0.281         | 0.281        | No        |
|                          | Manuf.–GVC DCR               | −0.067 **   | 0.031         | 0.054        | Yes       |
|                          | EHGW–GVC Participation       | 0.142 ***   | 0.001         | 0.004        | Yes       |
|                          | EHGW–GVC DCR                 | −0.089 **   | 0.013         | 0.038        | Yes       |
|                          | Mature–GVC Participation     | 0.085 ***   | 0.004         | 0.016        | Yes       |
|                          | Mature–GVC DCR               | 0.193 ***   | <0.001        | <0.001       | Yes       |
|                          | Growing–GVC Participation    | 0.022       | 0.491         | 0.382        | No        |
|                          | Growing–GVC DCR              | 0.041       | 0.352         | 0.308        | No        |
|                          | Recession.–GVC Participation | −0.041      | 0.255         | 0.257        | No        |
|                          | Recession.–GVC DCR           | −0.072      | 0.134         | 0.156        | No        |
|                          | Regener.–GVC Participation   | −0.028      | 0.397         | 0.338        | No        |
|                          | Regener.–GVC DCR             | −0.063 *    | 0.064         | 0.057        | Marginal  |
| Table 8 ( <i>m</i> = 2)  | GVC Forward                  | −0.695 ***  | <0.001        | 0.001        | Yes       |
|                          | GVC Backward                 | 0.311 ***   | <0.001        | 0.001        | Yes       |

Notes: \*, \*\*, and \*\*\* denote significance at the 10%, 5%, and 1% levels, respectively; *q*-values are Benjamini–Hochberg adjusted *p*-values within each family; family 1: causal mediation ACME tests (Table 6); family 2: heterogeneity subgroup coefficient tests (Table 7); family 3: GVC forward and backward participation tests (Table 8); FDR < 0.1 indicates whether the test remains significant after BH correction at the 10% false discovery rate threshold.

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