

Article

Study on the Impact of Virtual Agglomeration on the High-Quality Development of the New Energy Vehicle Industry

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Abstract

With the deepening development of the digital economy, new forms of industrial organization represented by virtual agglomeration are reshaping the logic of industry development. The purpose of this study is to empirically examine the impact of virtual agglomeration on the high-quality development of the new energy vehicle industry and its underlying mechanisms. Using panel data from 30 Chinese provinces covering the period 2018–2023, this study constructs two-way fixed-effects models, mediation models, moderation models, and threshold regression models. Employing econometric methods, it analyzes the direct impact of virtual agglomeration on the high-quality development of the new energy vehicle industry, as well as its mediation mechanisms, moderating effects, and nonlinear characteristics. Research findings reveal: (1) Virtual agglomeration promotes the high-quality development of the new energy vehicle industry, but its effects exhibit spatiotemporal heterogeneity. (2) Virtual agglomeration indirectly drives industrial development by enhancing technology market activity and promoting collaborative innovation. (3) The impact of virtual agglomeration exhibits a nonlinear pattern of increasing marginal returns and is positively regulated by the regional innovation environment. This paper expands the research perspective on virtual agglomeration and high-quality industrial development from both theoretical and empirical dimensions, providing policy recommendations for achieving high-quality development in the new energy vehicle industry during the digital economy era.

Keywords: high-quality development; new energy vehicle industry; virtual agglomeration



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1. Introduction

The transition of the traditional automotive industry toward new energy vehicles has become a shared trend in the global automotive sector. According to the International Energy Agency's (IEA) report *Global Electric Outlook 2023*, global electric vehicle sales exceeded 10 million units in 2022 and approached 14 million units in 2023, demonstrating strong growth momentum. It also represents a crucial strategic initiative for nations worldwide to address energy crises and global climate change while advancing the green and low-carbon transformation of their economies and societies. As the world's largest automotive market, China entered the new energy vehicle sector as early as the late 1990s. It views this as a crucial strategic opportunity to narrow the technological and industrial gap with developed nations in the automotive industry [1]. According to data from the International Organization of Motor Vehicle Manufacturers (OICA) and the

China Association of Automobile Manufacturers, China's automobile production exceeded 30.16 million units in 2023, marking the 14th consecutive year the country has ranked first globally. Of this total, production and sales of new energy vehicles reached 9.587 million and 9.495 million units, respectively, representing year-over-year increases of 35.8% and 37.9%, with a market share of 31.6%. Driven by the "Made in China 2025" strategy, China's new energy vehicle industry has experienced rapid development, with its overall level gradually approaching that of developed countries [2]. After experiencing policy-driven explosive growth, China's new energy vehicle industry is now at a critical crossroads, transitioning from "scale expansion" to "high-quality development". Despite China's introduction of multiple policies over the years to continuously promote the expansion and upgrading of the new energy vehicle industry, the sector still faces certain challenges amid its rapid growth. On the one hand, the traditional physical agglomeration model faces challenges such as rising land costs and worsening congestion, with diminishing marginal returns becoming increasingly evident. On the other hand, regional market fragmentation caused by administrative barriers hinders synergistic efficiency across the industrial chain, leading to innovation silos [3]. This makes it difficult to effectively carry out cross-regional joint research on key core technologies. The issues of being "large but not strong" and "comprehensive but not specialized" continue to constrain the high-quality development of the industry. Faced with increasingly fierce global competition and complex supply chain environments, relying solely on traditional approaches of accumulating factors and expanding physical space is no longer sustainable. Industries urgently need to explore new organizational models to break through the dual constraints of geography and resources.

As the new wave of technological revolution and industry transformation accelerates, the world is undergoing a profound and widespread digital transformation [4]. New-generation information technologies, represented by cloud computing, big data, artificial intelligence, and algorithmic technologies, are reshaping the organizational methods and spatial forms of economic activities. Virtual agglomeration, as a new spatial organization distinct from traditional geographic linkages, has emerged in response to the digital economy wave. It leverages digital networks to establish seamless connections across regions and among multiple entities, creating network effects that facilitate the optimized integration and efficient utilization of external resources [5]. The emergence of network synergies is dismantling the diseconomies of scale inherent in traditional management, spurring the rapid rise of platform economies [6]. Knowledge sharing and circulation processes have accelerated significantly; technological means have enabled the granular segmentation of production factors and processes into smaller units, facilitating more flexible and efficient combinations and allocations [7]. Digitalization of information has expanded the scope of production and transactions while reducing search and transaction costs. Enterprises utilize data aggregation and processing technologies to achieve global optimization of resource allocation, extending production activities into the global cyberspace [8]. The rise of virtual agglomeration has provided new pathways for industries to adapt and thrive in the digital economy era [9], increasingly becoming a vital driving force for the transformation, upgrading, and high-quality development of China's new energy vehicle industry. It is important to recognize that the digital transformation process itself presents challenges related to energy consumption; in the early stages, energy demand and consumption typically increase due to the expansion of data centers, network infrastructure, and computing needs [10]. By optimizing resource allocation, improving operational efficiency, and empowering smart energy management systems, virtual agglomeration may offer a viable path for reconciling digital transformation with sustainable energy consumption [11]. The tension between the energy demands driven by digitalization and the need for sustainable development also

underscores the importance of virtual agglomeration for the high-quality development of the new energy vehicle industry.

Against this backdrop, how does virtual agglomeration influence the high-quality development of China's new energy vehicle industry? What mediating mechanisms exist between the two? Does the impact of virtual agglomeration on the high-quality development of the new energy vehicle industry exhibit threshold effects? Does the regional innovation environment play a moderating role in this process? Are there regional heterogeneities in their influence, such as variations in digital infrastructure levels and temporal factors? Answering these questions will help clarify the relationship between virtual agglomeration and the high-quality development of the new energy vehicle industry. This, in turn, will facilitate the formulation of more rational industry support policies and more scientific innovation strategies, thereby assisting the new energy vehicle industry in overcoming development bottlenecks. Such insights hold significant theoretical and practical value.

The marginal contributions of this paper include: First, it expands the scope of application of the theory of virtual agglomeration to strategic emerging industries, reveals the mechanisms through which non-spatially constrained agglomeration influences the new energy vehicle industry, and addresses the shortcomings of traditional frameworks for analyzing geographic agglomeration. Second, existing literature primarily focuses on the impact of geographic agglomeration on single dimensions such as the innovation capacity and corporate performance of the new energy vehicle industry. This study constructs a comprehensive evaluation system that incorporates industry input intensity, output intensity, social drivers, and sustainability, and empirically examines the impact of virtual agglomeration on the high-quality development of the new energy vehicle industry, thereby enriching relevant theoretical research. Finally, in light of the intensified global competition in the new energy vehicle industry and the current predicament of China's industry being "big but not strong", the findings of this study can provide policymakers with actionable decision-making criteria and practical guidance for formulating targeted measures tailored to the specific characteristics of different regions and stages of development.

The remainder of this paper is structured as follows: Section 2 presents a literature review using an analytical approach, examining existing studies on industry agglomeration, virtual agglomeration and the new energy vehicle industry, while identifying gaps in current research. Section 3 outlines the theoretical framework and research hypotheses through a deductive approach. Section 4 describes data sources, the measurement of variables and econometric methodologies. Section 5 systematically presents the empirical test results of the model. Section 6 discusses the empirical results using inductive reasoning. Section 7 summarizes the recommendations, research limitations and future prospects.

2. Literature Review

2.1. Industry Agglomeration

Industry agglomeration is an important spatial organizational form of regional economic development; the formation and development of industry agglomeration theory can be traced back to Marshall's theory of industrial districts, proposed in the late 19th century [12]. This theory explains how spatial proximity generates synergistic economic benefits for firms within a region through mechanisms such as labor pools, the sharing of intermediate goods, and knowledge spillovers [13]. Building on this, Jacobs further proposed the concept of diverse externalities, emphasizing that the clustering and convergence of different industries can effectively promote the reconfiguration of knowledge and cross-industry innovation [14]. In the 1990s, Porter introduced the concept of industry agglomeration in *The Competitive Advantage of Nations* formally [15], positioning it as

a regional development strategy and laying the groundwork for subsequent research on industry agglomeration. Since the 21st century, related research has gradually diverged into two levels: industry and regional. At the industry level, Rosenthal noted that the geographic agglomeration of firms within the same industry can enhance productivity through three primary pathways: shared labor markets, shared intermediate inputs, and knowledge spillovers [16]. At the regional level, Martin's analysis of French manufacturing microdata indicated that industry spatial concentration is positively associated with productivity. However, these agglomeration effects remain largely localized, exhibiting limited spillovers across regions [17]. Aforementioned studies on traditional geographic agglomeration emphasize resource concentration in specific physical locations, which generates externalities through sharing, matching, and learning mechanisms [18], yet it may also induce congestion effects and rent-seeking behavior, adversely affecting long-term industry development [19]. With technological progress and globalization, the distance between people has been infinitely shortened [20], marking the "demise of distance" as a defining feature of the digital era [21], and network externalities, dominated by "flow spaces" are gaining precedence over agglomeration externalities constrained by "place spaces" [22]. Network externalities enable firms to leverage digital platforms, overcoming geographical limitations and facilitating collaboration, communication and resource sharing. This reduces efficiency losses resulting from uneven resource distribution [23] and enhances industry competitiveness. Against this backdrop, virtual agglomeration has emerged as a new form of industrial organization in the digital space.

2.2. Virtual Agglomeration

Virtual agglomeration, derived from Wilson's concept of cyberspace [24], was first proposed in 1997 by the EU-SACFA research consortium of seven universities. It refers to cross-industry firms forming virtual consortia in cyberspace to share market opportunities [25]. From different research perspectives, studies on virtual agglomeration have yielded diverse findings that intersect with and complement traditional research on industry agglomeration. Overall, existing research on virtual agglomeration focuses on two main areas: the theoretical implications of virtual agglomeration and quantitative analysis. Conceptually, Sumita et al. defined virtual agglomeration from the dispersion and technological dependency, describing it as an organizational form where geographically dispersed entities exchange information based on shared technologies [26]. Zerwas similarly argued that industry virtual agglomeration involves key players in industry chains concentrating in online spaces, driven by digitalization and intelligent transformation [27]. Although definitions vary in wording, their core meanings remain consistent and support further discussion of key characteristics. Soete indicated that virtual agglomeration has transformed traditional production and distribution models, forming complex systems composed of network modules [28]. Such systems are typically open, inclusive [29] and cross-spatial, enabling participants to engage in large-scale, low-cost and long-distance collaborative production and transactions [30].

Research on the role and functions of virtual agglomeration in application fields is also continuously expanding and improving. Romano et al. highlighted that virtual agglomeration breaks through spatial constraints, redefines economic activity boundaries, and facilitates the efficient circulation of production factors across wider regions [31]. Vakola and Wilson similarly argued that virtual agglomeration enables real-time collaboration and resource sharing, reducing transaction costs and improving production efficiency [32]. Kohtamäki et al. further confirmed that virtual agglomeration helps reduce various costs, including information search, negotiation, and performance monitoring [33]. From a global value chain perspective, Sturgeon emphasized that virtual agglomeration enables firms to

integrate more deeply into global knowledge networks and technological systems, strengthening their capacity for technology acquisition and innovation [34]. Peráček and Kaššaj analyzed the impact of digital connectivity and public administration on spatial organization from a European perspective, noting that digital infrastructure frameworks such as Industry 4.0, artificial intelligence, and autonomous driving are reshaping the development pathways of smart cities. They expanded the research perspective on advanced forms of virtual agglomeration in the digital context and their impact on industrial spatial layout [35]. Davis and Dingel provided empirical evidence that regions with higher levels of virtual agglomeration are associated with greater patenting efficiency and shorter new product development cycles than traditional agglomeration areas [36]. This suggests that virtual agglomeration extends and upgrades conventional geographically based agglomeration. As a salient feature of the digital economy, the mechanisms and development pathways of virtual agglomeration have attracted sustained attention. Azar and Ciabuschi reported that virtual agglomeration promotes industry innovation by facilitating inter-firm knowledge sharing and technology diffusion [37]. From a lean manufacturing perspective, virtual agglomeration strengthens supply chain collaboration to help firms move toward zero inventory and just-in-time production thereby improving resource utilization efficiency and market responsiveness [38]. Furthermore, from the perspective of economic security, the study by Ivančík and Dušek indicated that coordinated investment and policy interventions in strategic sectors can effectively mitigate systemic risks and enhance supply chain resilience. This perspective provides theoretical support for understanding the role of virtual agglomeration in enhancing competitiveness and strategic resilience within strategic emerging industries such as new energy vehicles [39].

Virtual agglomeration does not represent a disruption of traditional industrial clustering, but rather its extension and evolution into the digital space. Compared to traditional geographic agglomeration, virtual agglomeration exhibits significant differences and comparative advantages: First, in terms of spatial dimensions, traditional agglomeration is constrained by physical boundaries, which can easily lead to “crowding effects” such as rising land costs and environmental pollution. Virtual agglomeration, however, breaks through these geographic constraints, enabling cross-regional, networked, and borderless agglomeration based on digital platforms, with marginal costs approaching zero; Second, in terms of factor mobility and collaboration, traditional agglomeration relies on face-to-face knowledge spillovers and the dissemination of tacit knowledge, whereas virtual agglomeration, through digital technologies, drastically reduces information search and transaction costs, enabling upstream and downstream sectors of the industrial chain to achieve matching and synergy with exceptional efficiency. This evolution from the physical to the virtual space represents a major trend in the transformation of industrial organizational forms in the digital economy era.

2.3. Research Related to the Development of the New Energy Vehicle Industry

Given its notable potential for energy conservation and emission reduction, the new energy vehicle industry has become a focal point of global industry and academic research [40]. Consequently, studies on China’s new energy vehicle industry has expanded, aiming to analyze its development trends, identify key issues, and explore sustainable pathways. A large body of research suggests that the government’s differentiated policies were the key driver behind the early boom in China’s new energy industry. For example, Li identified the key obstacles facing the new energy vehicle industry and proposed countermeasures [41]. Furthermore, Zhang and Hu assessed the strengths, weaknesses, opportunities, and threats of China’s new energy vehicle industry, and proposed recommendations for enhancing its competitiveness [42]. In recent years, due to diversified policy support, China’s new

energy vehicle industry has rapidly grown into the world's largest market [43]. Michaela Kendall noted that environmental factors are one of the primary drivers behind the Chinese government's vigorous promotion of this industry [44]. Yuan et al. conducted a critical assessment of China's new energy vehicle policy framework and proposed constructive solutions for its future development [45]. Zhang analyzed 175 new energy vehicle policies implemented in selected Chinese regions between 2006 and 2016 using policy dependency mapping. The findings revealed that national-level policy objectives prioritized improving air quality, conserving fossil fuels, and revitalizing the automotive industry. In contrast, local policies focused more on developing charging infrastructure networks and addressing prominent regional challenges [46].

In addition, numerous scholars have conducted in-depth research on other factors influencing the development of the new energy vehicle industry. For example, Dargay et al. examined the impact of key factors such as vehicle ownership, GDP, and population structure on industrial development [47]. Meng's research indicates that factors such as R&D investment, technological innovation capacity, market size, financial support, and human resources have a positive impact on industrial development [48]. Hu employed a gravity model to demonstrate that carbon emission levels, GDP, and distance are the primary factors influencing the trade potential of China's new energy vehicles in Belt and Road countries, with China exhibiting significant trade potential in this sector [49], providing valuable insights for industry internationalization. Zulfiqar et al. took Pakistan as an example to explore opportunities related to the development of charging infrastructure, the design of financial subsidies, and industrial synergy, providing an important international comparative perspective for understanding strategies for promoting the new energy vehicle industry under different institutional environments and market conditions [50].

Existing research has thoroughly demonstrated the necessity of developing the new energy vehicle industry and has examined the impact of various factors on individual indicators such as industry performance, innovation capacity, and export trade. However, few studies have incorporated multidimensional indicators into a unified framework to comprehensively assess the level of high-quality development in the new energy vehicle industry. Furthermore, current research primarily adopts the perspective of traditional industry agglomeration, and the mechanisms through which virtual agglomeration—an emerging form of industrial organization—influences the new energy vehicle industry have not yet received sufficient attention. However, the new energy vehicle industry is characterized by a long industrial chain, rapid technological iteration, and high demands for collaboration. These characteristics create a strong need for knowledge sharing across geographical boundaries and real-time supply chain coordination. In this context, exploring how virtual agglomeration can restructure the industrial chain and address the shortcomings of traditional geographical agglomeration is of great significance for promoting the high-quality development of this industry.

2.4. Summary and Research Gaps

Existing research provides a foundation for understanding the evolution of industry organization forms in the digital economy, but discussions surrounding virtual agglomeration and its impact on the new energy vehicle industry remain insufficient. On the one hand, although the theoretical implications, characteristics, and mechanisms of virtual agglomeration have been preliminarily elucidated, related analyses remain predominantly normative or descriptive in nature. There is a lack of quantitative empirical analysis targeting specific industries, particularly research on virtual agglomeration within the new energy vehicle industry. On the other hand, while prior research on the new energy vehicle industry has examined its development necessity and factors influencing single

indicators such as industry performance, innovation capacity, and export trade, few studies have established a comprehensive, multidimensional evaluation system to assess overall high-quality development. Moreover, as an emergent organizational form, the role and mechanism of virtual agglomeration in fostering this development remain underexplored. Overall, existing literature primarily analyzes the industry through traditional lenses such as geographic agglomeration or technological investment. However, systematic empirical evidence on how platform-based agglomeration shapes the high-quality development of the new energy vehicle industry remains sparse. In light of this, this study constructs a multidimensional evaluation system for the high-quality development of the new energy vehicle industry and empirically investigates the impact and mechanisms of virtual agglomeration, aiming to expand the research boundaries of virtual agglomeration and offer theoretical and policy insights for advancing the high-quality development of the new energy vehicle industry.

3. Theoretical Analysis and Hypothesis Development

3.1. Direct Impact of Virtual Agglomeration on the High-Quality Development of the New Energy Vehicle Industry

Virtual agglomeration reduces industries' dependence on geographic space and accelerates the development of networks without geographical constraints [51]. By breaking down geographical barriers, it strengthens information connectivity and resource sharing among enterprises, providing a vital platform for the cross-regional flow of factors and collaborative innovation. Akerlof argues that information superiority is crucial in economic activities [52]. Virtual agglomeration amplifies positive externalities by enabling real-time, low-cost information exchange among enterprises across regions. This facilitates the integration and sharing of critical factors such as technology, capital, and data, thereby reducing information asymmetry and driving technological advancement and structural optimization within the new energy vehicle industry. In addition, virtual agglomeration can also enhance coordination between upstream and downstream segments of the industrial chain, deepen specialization, and drive value chain upgrading [53], thereby propelling the new energy vehicle industry's transition from scale expansion to quality enhancement. Finally, empirical research has shown that once geographic concentration reaches a certain level, it gives rise to negative externalities such as rising congestion costs and soaring land prices [54]. When congestion effects are taken into account, the benefits of agglomeration significantly diminish [55], all of which constrain further industrial development. Internet platforms, however, do not impose limits on the number of entities involved, thereby avoiding the negative impacts associated with excessive concentration in geographic agglomeration [56]. Therefore, this paper argues the following:

H1. *Virtual agglomeration has a positive effect on the high-quality development of the new energy vehicle industry.*

3.2. Indirect Impact of Virtual Agglomeration on the High-Quality Development of the New Energy Vehicle Industry

In the context of the digital economy, industry agglomeration is shifting from traditional models reliant on geographic proximity to virtual agglomeration based on digital platforms [57]. On the one hand, virtual agglomeration leverages extensive digital connectivity and information platforms to effectively mitigate information asymmetry between technology suppliers and demanders [58], thereby reducing transaction costs. This boosts the dynamism of technology markets, accelerates the diffusion and commercial application of key technologies in the new energy vehicle sector, and empowers high-quality industry development. On the other hand, virtual agglomeration builds cross-regional

online collaboration networks, providing efficient coordination channels for diverse innovation actors. This strengthens R&D cooperation intensity, promotes the integration of innovation resources, joint research on core technologies, and knowledge spillovers [59]. Consequently, it drives collaborative innovation processes and injects innovative momentum into high-quality industrial development. For the new energy vehicle industry, which is both technology-intensive and innovation-driven, virtual agglomeration facilitates a shift from scale expansion to quality enhancement. Based on the aforementioned mechanisms, this paper argues that virtual agglomeration also indirectly empowers the development of the new energy vehicle industry by boosting technology market activity and accelerating collaborative innovation. Hence, the following research hypothesis is proposed:

H2. *Virtual agglomeration indirectly promotes the high-quality development of the new energy vehicle industry by enhancing technology market activity and accelerating collaborative innovation magnitude.*

3.3. Nonlinear Characteristics of Virtual Agglomeration in Promoting High-Quality Development of the New Energy Vehicle Industry

The impact of virtual agglomeration on the high-quality development of the new energy vehicle industry may exhibit nonlinear characteristics, a conclusion primarily grounded in Rohlfs' theory of network externalities. He pointed out that when the value of a product increases as the number of users grows, network externalities exist [60]. Katz and Shapiro transformed this theoretical system into an economic framework, which has been widely applied in telecommunications, software, internet platforms, and other fields [61]. Subsequently, Metcalfe described the economic phenomenon where a network's value grows quadratically with the number of nodes, summarizing it as "Metcalfe's Law" [62]. Empirical research shows that Metcalfe's Law holds true for Internet usage patterns, and that network value does indeed exhibit nonlinear growth [63]. Virtual agglomeration, grounded in the internet and formed through digital platforms as networked organizations, inherently possesses network externalities. Consequently, their effectiveness may vary across different developmental stages. At lower levels of virtual agglomeration, platform functionality remains underdeveloped and network connectivity density is low. Limited interaction and collaboration among enterprises prevent the full realization of advantages in information sharing and resource allocation [64], resulting in a relatively weak promotional effect on the high-quality development of the new energy vehicle industry. As the level of virtual agglomeration increases, network economies of scale and synergistic effects gradually emerge. Connections among diverse entities within the new energy vehicle industry chain become increasingly tight, enhancing the efficiency of information flow and resource integration, thereby amplifying marginal promotion effects. Once virtual agglomeration reaches a certain level, platform rules mature, network externalities and learning effects accumulate continuously [61]. This amplifies knowledge spillovers and collaborative innovation effects, thereby accelerating technological advancement and development quality in the new energy vehicle industry. Correspondingly, this paper argues the following:

H3. *The impact of virtual agglomeration on the high-quality development of the new energy vehicle industry exhibits a non-linear characteristic with increasing marginal effects.*

3.4. Based on the Moderating Effect of the Regional Innovation Environment

The impact of virtual agglomeration on the development of the new energy vehicle industry does not exist in isolation but is jointly constrained by regional institutional environments and technological conditions, with the regional innovation environment

serving as a representative moderating factor [65]. The regional innovation environment reflects a region's institutional foundations, resource endowments, and ecosystem vitality in knowledge creation, technological R&D, and achievement transformation, often comprehensively measured through indicators such as R&D intensity and innovation output levels [66]. A robust regional innovation environment provides essential support for virtual agglomeration, enabling its network connections and platform collaboration mechanisms to translate more effectively into industrial development outcomes. In regions with superior innovation environments, enterprises demonstrate stronger capabilities in knowledge absorption and technology conversion. Consequently, the information sharing, collaborative R&D, and knowledge spillover effects generated by virtual agglomeration are more readily absorbed and transformed [67], thereby enhancing their promotional role in the high-quality development of the new energy vehicle industry. Based on this, the following hypothesis is proposed:

H4. *Regional innovation environment positively mediates the relationship between virtual agglomeration and the high-quality development of the new energy vehicle industry.*

4. Model Design and Variable Selection

4.1. Data Sources

This study covers 30 provinces (autonomous regions and municipalities) in China from 2018 to 2023 as the research sample, excluding Tibet, Hong Kong, Macao, and Taiwan due to data availability constraints. Data sources include the National Bureau of Statistics, China Statistical Yearbook, China Industrial Statistical Yearbook, and provincial statistical yearbooks. These data are released by official agencies such as the National Bureau of Statistics and the Ministry of Industry and Information Technology, as well as authoritative research organizations, and have undergone rigorous quality control and verification procedures. A small number of missing values are imputed using logarithmic linear interpolation. Descriptive statistics for the variables are presented in Table 1.

Table 1. Descriptive Statistics of Variables.

Variables	N	Mean	Std. Dev.	Min	Max
Nevd	180	0.137	0.128	0.002	0.871
VA	180	0.852	0.735	0.348	4.364
Pop	180	8.219	0.743	6.375	9.450
Traff	180	1.934	0.310	1.018	2.641
FDI	180	0.016	0.019	0.001	0.101
Eff_k	180	1.670	1.091	0.672	5.495
ER	180	0.002	0.002	0.001	0.008
Tech_Market	180	0.028	0.037	0.000	0.195
CIM	180	0.741	0.979	0.021	5.908
Innov	180	0.135	0.191	0.000	1.000

4.2. Variable Measurement

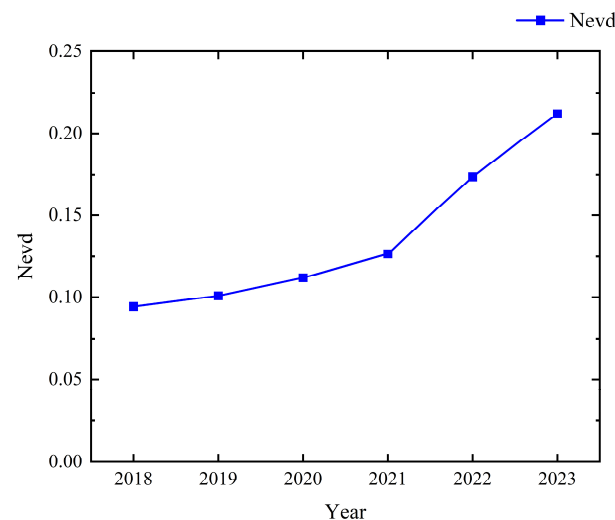
4.2.1. Dependent Variable

High-Quality Development of the New Energy Vehicle Industry (Nevd). This paper reviews existing literature on evaluation indicator systems for high-quality development by other scholars [68,69] and references relevant studies on the new energy vehicle industry. Based on these, a comprehensive evaluation framework is constructed using 13 indicators across four dimensions. The entropy weight method is applied to calculate the high-quality development indices for the new energy vehicle industry. Specific indicators are detailed in Table 2.

Table 2. Measurement and Evaluation System for High-Quality Development of the New Energy Vehicle Industry.

Guideline Layer	Indicator Layer	Indicator Explanation
Industry Investment Intensity	Human Capital	A1 Student headcount in regular higher education institutions
	Digital Technology	A2 Digital inclusive finance index
	Value-Added Protection	A3 Number of public charging stations
	Industrial Base	A4 Automotive manufacturing output value
Industry output intensity	Employment-driven	B1 Employment in the automotive manufacturing industry
	Production Capacity	B2 New energy vehicle production
	Industry Development	B3 Number of listed companies in the new energy sector
Social Drivers	Purchasing Power	C1 Permanent resident population
	Policy Support	C2 Per capita disposable income
		C3 Number of new energy vehicle policies
Sustainable Development	Green Transition	D1 Number of green factories in the automotive manufacturing industry
	Recycling Capacity	D2 Number of enterprises meeting the comprehensive utilization standards for power batteries
	Promotion and Application	D3 Year-end stock of new energy vehicles

Based on the aforementioned evaluation indicator system and the results calculated using the entropy weight method, this paper further plots the annual trend chart of the high-quality development level of the new energy vehicle industry across China's 30 provinces from 2018 to 2023 (as shown in Figure 1). This chart visually illustrates the overall evolution trajectory of the high-quality development level of the new energy vehicle industry during the sample period, providing preliminary support for subsequent empirical analysis.

**Figure 1.** Trend Chart of High-Quality Development in China's New Energy Vehicle Industry from 2018 to 2023.

4.2.2. Explanatory Variable

Virtual Agglomeration (VA). Although virtual agglomeration is unconstrained by physical space, its core elements, digital technology, data resources, and digital talent still require specific industrial sectors to realize economic value conversion. By measuring the relative density of employment in information transmission, computer services, and software industries, we can effectively capture a region's resource foundation and activity level in virtual agglomeration. Therefore, drawing on classical regional economic theory, this

paper utilizes the location entropy index to calculate each province's virtual agglomeration level. The specific calculation formula is:

$$VA_{it} = \frac{VS_{it}/X_{it}}{VS_t/X_t}$$

Here, VA_{it} represents the virtual agglomeration level of region i in year t ; VS_{it} denotes the employment in the information transmission, computer services, and software industry of region i in year t ; X_{it} denotes the total employment in region i in year t ; VS_t represents the employment in the information transmission, computer services, and software industry across all regions; X_t refers to the total employment.

Figure 2 illustrates the average spatial distribution of virtual agglomeration indices across Chinese provinces from 2018 to 2023. The data reveals that eastern coastal regions and certain central provinces exhibit higher levels of virtual agglomeration, while western regions generally maintain lower levels. The Beijing-Tianjin-Hebei region demonstrates the highest agglomeration intensity, forming distinct spatial heterogeneity.

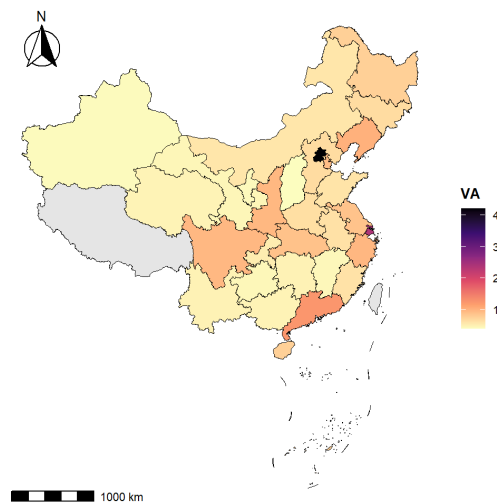


Figure 2. Virtual Agglomeration Levels Across Chinese Provinces from 2018 to 2023.

4.2.3. Control Variables

To more accurately identify the impact of virtual agglomeration on the development of the new energy vehicle industry, the following control variables are introduced in the empirical analysis: (1) Population size (Pop), measured by the logarithm of the year-end total population. (2) Traffic Infrastructure (Traff), represented by the logarithm of per capita urban road area. (3) Foreign Direct Investment (FDI), calculated as the proportion of foreign investment to regional GDP. (4) Capital Efficiency (Eff_K), measured by the ratio of regional GDP to fixed asset investment, reflects the efficiency of capital allocation and utilization. (5) Environmental regulation (ER), measured as the ratio of investment in industrial pollution control to industrial value added, reflects the intensity of environmental protection efforts in a region.

4.2.4. Mediating Variables

- (1) Technology Market Activity (Tech_Market). This study employs the ratio of technology market transaction volume to GDP as a measure of technology market activity. This metric objectively reflects the transaction dynamism of visible technological achievements within a region and the efficiency of market-based allocation of technological factors, serving as an effective proxy variable for knowledge spillovers across entities and regions.

- (2) Collaborative Innovation Magnitude (CIM). The level of collaborative innovation is measured by the number of joint patent applications.

4.2.5. Moderating Variable

Regional Innovation Environment (Innov). This paper employs the entropy weight method to conduct a comprehensive measurement of R&D expenditures and patent applications. The definition of each variable and the measurement methods are shown in Table 3.

Table 3. Variable Definition and Measurement.

Variables	Name	Symbol	Measurement
Dependent variable	High-Quality Development of the New Energy Vehicle Industry	Nevd	Using the entropy weight-TOPSIS method based on Table 1
Explanatory variable	Virtual Agglomeration	VA	$VA_{it} = \frac{VS_{it}/X_{it}}{VS_t/X_t}$
Control variables	Population Size	Pop	Logarithm of the year-end population
	Traffic Infrastructure	Traff	Logarithm of per capita urban road area
	Foreign Direct Investment	FDI	Ratio of Foreign Investment to GDP
	Capital Efficiency	Eff_K	Ratio of GDP to Fixed Asset Investment
Mediating variables	Environmental Regulation	ER	Ratio of investment in industrial pollution control to industrial value added
	Technology Market Activity	Tech_Market	Ratio of Technology Market Transaction Volume to GDP
	Collaborative Innovation Magnitude	CIM	Collaborative Patent Applications (10,000 units)
Moderating variable	Regional Innovation Environment	Innov	The weighted average of R&D expenditure and patent applications.

4.3. Econometric Models

To examine Hypothesis 1, this study first establishes a panel data model to explore the influence of virtual agglomeration on the high-quality development of the new energy vehicle industry, as shown in Equation (1):

$$Nevd_{it} = \alpha_0 + \alpha_1 VA_{it} + \alpha_2 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Among them, the dependent variable $Nevd_{it}$ respectively represents the degree of high-quality development in the new energy vehicle industry in region i during year t ; VA_{it} denotes the level of virtual agglomeration in region i during year t ; $Control_{it}$ signifies the set of control variables; α stands for the constant and coefficients; μ_i and λ_t denote individual and time fixed effects; ε_{it} is a random disturbance term.

Moreover, this paper further investigates the indirect impact between virtual agglomeration and the high-quality development of the new energy vehicle industry. Building upon Model (1), the stepwise analysis method proposed by Baron and Kenny [70] is employed to construct the following mediation effect model. Models (1)–(3) collectively form the stepwise regression mediation effect model:

$$Med_{it} = \beta_0 + \beta_1 VA_{it} + \beta_2 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (2)$$

$$Nevd_{it} = \theta_0 + \theta_1 VA_{it} + \theta_2 Med_{it} + \theta_3 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (3)$$

Herein, Med_{it} refers to mediating variables, which are corporate technology market activity and collaborative innovation magnitude. The meanings of other variables are the same as in Model (1).

To verify Hypothesis 3 and explore whether virtual agglomeration exerts a nonlinear effect on the high-quality development of the new energy vehicle industry, a threshold effect regression model is employed. The formula is as follows:

$$Nevd_{it} = \delta_0 + \delta_1 VA_{it} \cdot I(VA_{it} \leq \gamma) + \delta_2 VA_{it} \cdot I(VA_{it} > \gamma) + \delta_3 Control_{it} + \mu_i \quad (4)$$

In this equation, $I(\cdot)$ is an indicator function, which takes the value 1 when the condition in parentheses is satisfied and 0 otherwise; γ represents the threshold value; δ denotes the constant and coefficient.

Finally, this paper introduces an interaction term between virtual agglomeration and regional innovation environment into the baseline regression model to examine whether the role of virtual agglomeration in the development of the new energy vehicle industry is moderated by the regional innovation environment, the following moderation effect model is constructed:

$$Nevd_{it} = \rho_0 + \rho_1 VA_{it} + \rho_2 Innov_{it} + \rho_3 VA_{it} \times Innov_{it} + \rho_4 Control_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (5)$$

where $Innov_{it}$ serves as a moderating variable for the regional innovation environment, while $VA_{it} \times Innov_{it}$ represents the interaction term between virtual agglomeration and the regional innovation environment. We use Stata 18.0 for the regression analysis.

5. Empirical Result and Analysis

5.1. Benchmark Regression

Table 4 reports the benchmark regression results of VA on the Nevd. Column (1) presents the estimation results including only core explanatory variables, while Columns (2)–(6) progressively incorporate control variables. All regressions control for fixed effects of individual and time to eliminate the influence of unobservable individual heterogeneity and time trends as much as possible.

Table 4. Benchmark Regression Results.

Variables	Nevd					
	(1)	(2)	(3)	(4)	(5)	(6)
VA	0.220 *** (0.050)	0.187 *** (0.051)	0.184 *** (0.052)	0.156 *** (0.051)	0.158 *** (0.051)	0.157 *** (0.051)
Pop		0.787 ** (0.332)	0.818 ** (0.335)	1.131 *** (0.340)	1.124 *** (0.341)	1.161 *** (0.341)
Traff			−0.045 (0.053)	−0.050 (0.051)	−0.047 (0.052)	−0.077 (0.055)
FDI				−1.502 *** (0.482)	−1.541 *** (0.491)	−1.537 *** (0.489)
Eff_K					0.014 (0.030)	0.021 (0.030)
ER						5.222 (3.498)
_Cons	−0.826 *** (0.214)	−6.737 *** (2.504)	−6.887 *** (2.513)	−9.114 *** (2.541)	−9.140 *** (2.549)	−9.415 *** (2.545)
Province FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
<i>n</i>	180	180	180	180	180	180
R-squared	0.9104	0.9137	0.9142	0.9197	0.9198	0.9211

Notes: *** $p < 0.01$, ** $p < 0.05$.

The regression results indicate that the coefficients for VA are positive across all columns and pass statistical tests at the 1% significance level. Regarding overall model performance, the R^2 values for each regression column exceeded 0.91. The model's explanatory power steadily increased with the sequential inclusion of control variables, indicating good fit and robustness of the regression results. These findings demonstrate that, after controlling for relevant influencing factors, VA exerts a stable promotional effect on the Nevd, preliminarily validating Hypothesis 1 of this study.

5.2. Mechanism Analysis

To further reveal the underlying mechanism through which VA influences the Nevd, this study introduces Tech_Market and CIM as mediating variables. It tests whether VA promotes the Nevd by stimulating technological market vitality and fostering collaborative innovation magnitude. Columns (1) to (6) of Table 5 presents the mechanism test results.

Table 5. Results of Mechanism Analysis and Moderating Effect Tests.

Variables	Mechanism Analysis					Moderation Effect	
	(1) Nevd	(2) Tech_Market	(3) Nevd	(4) Nevd	(5) CIM	(6) Nevd	(7) Nevd
VA	0.161 *** (0.051)	0.024 * (0.014)	0.139 *** (0.050)	0.161 *** (0.051)	0.945 *** (0.159)	0.112 * (0.057)	0.103 *** (0.034)
Innov							0.921 *** (0.080)
VA*Innov							0.354 *** (0.138)
Pop	1.147 *** (0.341)	0.137 (0.091)	1.018 *** (0.334)	1.147 *** (0.341)	0.140 (1.058)	1.139 *** (0.338)	0.158 (0.235)
Traff	−0.066 (0.054)	−0.020 (0.014)	−0.047 (0.053)	−0.066 (0.054)	−0.718 *** (0.167)	−0.028 (0.057)	0.045 (0.036)
FDI	−1.572 *** (0.490)	−0.513 *** (0.131)	−1.092 ** (0.502)	−1.572 *** (0.490)	−0.565 (1.522)	−1.542 *** (0.486)	−0.895 *** (0.325)
Eff_k	0.013 (0.030)	−0.001 (0.008)	0.014 (0.029)	0.013 (0.030)	0.347 *** (0.092)	−0.005 (0.031)	0.020 (0.021)
ER	5.268 (4.123)	1.949 * (1.103)	3.449 (4.052)	5.268 (4.123)	36.838 *** (12.800)	3.344 (4.203)	0.646 (2.765)
Tech_Market			0.934 *** (0.308)				
CIM						0.052 * (0.027)	
_Cons	−9.299 *** (2.546)	−0.882 (0.686)	−8.421 *** (2.491)	−9.299 *** (2.546)	−0.724 (7.904)	−9.261 *** (2.522)	−1.677 (1.760)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
<i>n</i>	180	180	180	180	180	180	180
R-squared	0.921	0.929	0.926	0.921	0.987	0.923	0.967

Notes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

In the baseline regression without mediating variables in Column (1), the regression coefficient for VA on Nevd is 0.161, significant at the 1% level. This indicates that VA directly promotes the Nevd, providing a foundation for testing the mediating effect. Column (2) demonstrates the impact of VA on Tech_Market, with a coefficient of 0.024, significant at the 10% level. This indicates that VA enhances Tech_Market by reducing information asymmetry and transaction costs. Column (3) incorporates the mediating variable Tech_Market into the baseline model. The results show that the Tech_Market coefficient is 0.934 and significant at the 1% level, indicating that increased Tech_Market drives high-quality indus-

trial development and partially mediates the relationship between VA and Nevd. That is, VA enhances Nevd indirectly by boosting the vitality of the technology transaction market.

Column (5) indicates that VA has a positive effect on CIM, demonstrating that VA mitigates spatio-temporal constraints on collaborative R&D by establishing digital collaboration networks, thereby improving knowledge sharing and joint R&D efficiency among innovation entities. Column (6) shows that CIM also promotes Nevd, suggesting that knowledge integration and technological breakthroughs achieved through joint R&D can directly enhance industrial technological capabilities and competitiveness. This highlights the crucial role of VA in fostering network effects within collaborative innovation. Overall, VA indirectly promotes the Nevd through enhancing technology market activity and accelerating collaborative innovation, thereby validating Hypothesis 2.

5.3. Threshold Effect

Given that the relationships among economic variables are often non-linear, the impact of VA on Nevd may exhibit threshold effects. Building upon the linear model presented earlier, this study employs the level of virtual agglomeration as a threshold variable and utilizes Hansen's panel threshold regression model [71] for empirical testing to identify potential threshold effects. The results of the threshold effect test are presented in Table 6.

Table 6. Threshold Effect Test.

Threshold Test	Number of Thresholds	F Value	<i>p</i> Value	10% Threshold	5% Threshold	1% Threshold
Single threshold	One threshold	45.52	0.003	17.159	19.897	26.406
Double threshold	One threshold	45.52	0.000	16.212	18.912	24.243
	Second Threshold	7.70	0.3675	62.245	83.372	112.569

The threshold effect test results indicate that the F-value for the single threshold test is 45.52, which is significant at the 1% level. This value is substantially higher than the 1% critical value (27.3468), confirming the presence of a significant single threshold effect. In the dual-threshold test, the F-value for the second threshold is 7.70 with a *p*-value of 0.3675, failing to pass the 10% significance level test. This indicates no dual threshold exists within the sample interval. Therefore, this study adopts the single-threshold model to analyze the nonlinear effects of virtual agglomeration.

Figure 3 reveals a distinct “V”-shaped pattern near the threshold value, with the lowest point corresponding to the virtual agglomeration level representing the threshold estimate value. When the LR statistic falls below the horizontal dashed line, that is, the critical value at the 5% significance level, the corresponding interval constitutes the 95% confidence interval of the threshold estimate value. The graphical results show that the LR curve drops significantly near the threshold value and crosses the critical line, further confirming the existence of the threshold effect.

Based on this, this paper analyzes the threshold regression results in Table 7, revealing that the threshold value for virtual agglomeration is 1.2411. When the level of virtual agglomeration falls below the threshold value ($VA \leq 1.2411$), the coefficient of VA's impact on the Nevd is 0.066 and fails to pass the significance test. It indicates that at a low level of VA, its promotional effect on the Nevd is not pronounced. However, when the VA level exceeds the threshold ($VA > 1.2411$), the coefficient of VA rises to 0.249 and becomes statistically significant at the 1% level. This indicates that the promotional effect of VA on the Nevd significantly intensifies beyond the threshold, exhibiting distinct phased and nonlinear characteristics.

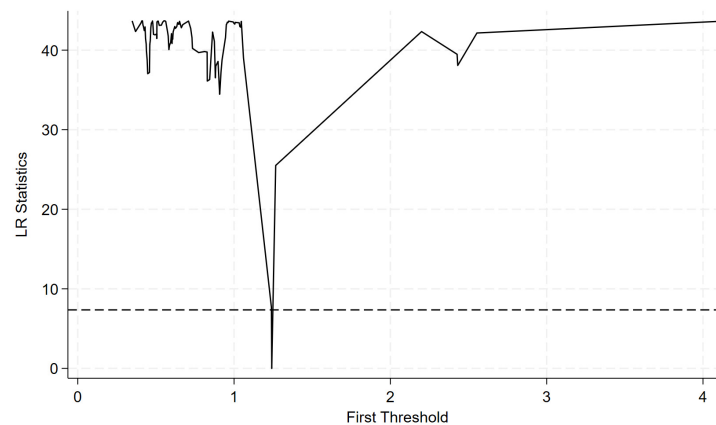


Figure 3. Likelihood Ratio Test Function Curve under the 95% Confidence Interval for the Threshold Effect.

Table 7. Threshold Effect Regression Results.

Variables	Threshold Variable
	VA
Threshold value (ql)	1.2411
Below the threshold value ($Th \leq ql$)	0.066 (0.073)
Above the threshold value ($Th > ql$)	0.249 *** (0.071)
n	180
R-squared	0.528

Note: *** $p < 0.01$.

From an economic perspective, the establishment and operation of VA typically involve high fixed costs and initial investments. At lower levels of agglomeration, the limited number of participants and insufficient network connectivity density prevent the full realization of network effects, knowledge spillovers, and collaborative innovation effects, thereby weakening their capacity to drive the development of the new energy vehicle industry. As the level of VA continues to rise, the number of platform nodes and the strength of connections increase. Metcalfe's Law suggests that the worth of the network scales with the square of its users. This leads to a marked improvement in the efficiency of knowledge and information flow, thereby strengthening technology diffusion, innovation collaboration, and industrial chain cooperation. Ultimately, this generates a promotional effect on the Nevd.

In summary, the impact of VA on the Nevd is not linearly increasing but exhibits a threshold effect. Only when the level of VA reaches a certain critical threshold can its promotional role in Nevd be fully unleashed through network effects and knowledge spillover mechanisms. Hypothesis 3 is thus validated.

5.4. Moderating Effects of Regional Innovation Environment

The results of the moderation effect are shown in column (7) of Table 5. The coefficient for VA is 0.103, significant at the 1% level, suggesting that VA continues to promote the Nevd even after controlling for the moderating variable. The coefficient for the Innov is also significantly positive at the 1% level, indicating that it exerts a positive influence on the Nevd. The interaction coefficient between VA and Innov ($VA \times Innov$) is 0.354 and significant at the 1% level, indicating that the Innov exerts a positive moderating effect on the promotion of Nevd through VA. Specifically, in regions with a stronger innovation

atmosphere and more concentrated innovation resources, VA exerts a stronger promotional effect on the Nevd. Hypothesis 4 is thus validated.

5.5. Robustness Tests

To minimize the possible effects arising from sample outliers, measurement biases in variables and omission of key control variables on conclusions, this study conducted robustness tests on the results using 1% winsorization [72], replacing the dependent variable [73], add control variable [74], replacing explanatory variables [74] and one-period lag [75].

5.5.1. 1% Winsorization

Two-tailed 1% tail trimming is applied to the primary continuous variables to eliminate the interference of extreme observations on the regression outcomes, ensuring conclusions remain unaffected by anomalous samples. Based on this adjustment, the benchmark regression model is re-estimated, with results presented in Column (1) of Table 8.

Table 8. Robustness Test.

Variables	(1) 1% Winsorization	(2) Replacing the Dependent Variable	(3) Add Control Variable	(4) Replacing the Explanatory Variable	(5) One-Period Lag
VA	0.156 *** (0.045)	2.613 *** (0.779)	0.152 *** (0.051)	2.592 ** (1.359)	0.163 *** (0.064)
Controls	Yes	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
<i>n</i>	180	180	180	180	180
Adjusted R ²	0.9144	0.8958	0.8990	0.8935	0.9000

Notes: ** $p < 0.05$, *** $p < 0.01$.

5.5.2. Replacing the Dependent Variable

In benchmark regression, this paper employs the entropy weight method to measure the level of high-quality development in the new energy vehicle industry. Although the entropy weight method can mitigate biases arising from subjective weighting to some extent, its results may still be influenced by indicator selection and weighting methodologies. To this end, principal component analysis (PCA) is applied to perform dimensionality reduction on the existing 13 indicators. A composite index for the high-quality development of the new energy vehicle industry is then reconstructed as a substitute indicator for the dependent variable. Regression analysis is re-conducted under the same model settings, with the results shown in Column (2) of Table 8.

5.5.3. Add Control Variables

In the benchmark regression model, this paper has controlled for several key factors influencing the Nevd. Regional industrial structure differences may also exert impacts on the Nevd by affecting resource allocation efficiency, factor mobility, and technological upgrading pathways. Therefore, this study further introduces the industrial structure upgrading index as an additional control variable. This indicator measures the ratio of tertiary industry value-added to secondary industry value-added, capturing the degree of regional industrial structure upgrading from traditional manufacturing to high-end industries. While maintaining the model specification, sample scope, and fixed effects

unchanged, the baseline model was re-estimated. The regression results are shown in Column (3) of Table 8.

5.5.4. Replacing Explanatory Variables

To test the robustness of the baseline regression results, this paper re-measures the level of VA using alternative indicators. Drawing on the research by Shen et al. [76], we construct a virtual agglomeration index that comprehensively considers both the degree of industry agglomeration and digital infrastructure. Calculate the degree of industry agglomeration in each region using location entropy, and then multiply this value by the weight of Internet ports. The specific formula is $VA_{it} = (\frac{VS_{it}}{X_{it}}) / (\frac{VS_t}{X_t}) \times (\frac{Net_{it}}{Net_t})$. This index provides a more comprehensive reflection of the overall characteristics of virtual agglomeration. The results of the re-estimation, conducted with the model specifications remaining unchanged, are presented in Column (4) of Table 8.

5.5.5. One-Period Lag

Given that the impact of VA on the Nevd may be subject to a time lag, this paper employs the one-period lagged VA index as an explanatory variable to conduct a robustness test. This approach aligns with the dynamic adjustment patterns of economic activity and, to some extent, mitigates endogeneity issues arising from reverse causality. With all other control variables, fixed effects, and the sample scope held constant, the model is re-estimated, and the regression results are presented in column (5) of Table 8.

The results consistently demonstrate significant positive effects, confirming the robustness of the conclusion that VA positively promotes the Nevd.

5.6. Heterogeneity Analysis

5.6.1. Temporal Heterogeneity

The manifestation of virtual agglomeration effects is not static but deeply dependent on the technological infrastructure and macro-policy environment upon which it relies. To examine the dynamic evolution of virtual agglomeration's impact on the high-quality development of the new energy vehicle industry and identify the moderating role of major policy shocks, this study uses the 2020 national policy white paper explicitly proposing the "new infrastructure" strategy as a dividing point. The sample period is divided into two phases: 2018–2019 (pre-policy) and 2020–2023 (policy implementation), with separate regression analyses conducted for each.

The regression results are shown in columns (1) and (2) of Table 9. The coefficient for VA exhibits a fundamental shift across the two phases. During 2018 to 2019, VA's coefficient is -0.062 and significant at the 5% level. This indicates that in the early stages of digital infrastructure development, the costs of establishing and coordinating virtual agglomeration may temporarily exceed the network benefits generated, exerting a slight inhibitory effect on industrial development. However, from 2020 to 2023, the coefficient for VA shifted to 0.223 , highly significant at the 1% level. This suggests that with the implementation and advancement of the "New Infrastructure" policy, bottlenecks in digital infrastructure have been effectively alleviated. Consequently, the network effects, knowledge spillovers, and collaborative innovation potential of virtual agglomeration have been fully unleashed, promoting the high-quality development of the new energy vehicle industry.

Table 9. Heterogeneity Analysis.

Variables	(1)	(2)	(3)	(4)
	2018–2019	2020–2023	Low-Level Regions	High-Level Regions
VA	−0.062 ** (0.026)	0.223 *** (0.079)	0.111 *** (0.045)	0.278 ** (0.125)
Controls	Yes	Yes	Yes	Yes
Province	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
<i>n</i>	60	120	90	90
Adjusted R ²	0.9976	0.9409	0.9269	0.8957

Notes: ** $p < 0.05$, *** $p < 0.01$.

5.6.2. Regional Heterogeneity

Digital infrastructure serves as the critical physical foundation for information flow, online collaboration, and data-driven empowerment. Its development level directly constrains the operational efficiency and scope of virtual agglomeration. Therefore, based on the average level of digital infrastructure across provinces during the sample period, this study groups the sample into “low-level regions” and “high-level regions” for separate regression analysis. The estimation results are presented in columns (3) and (4) of Table 9.

The estimated coefficient for VA is 0.1109 in low-level areas and rises to 0.2781 in high-level areas; both are statistically significant at the 5% level, with the latter coefficient being approximately 2.5 times that of the former. This disparity indicates that the promoting effect of VA on the NEVD is highly dependent on the sophistication of regional digital infrastructure. A well-established digital foundation facilitates cross-regional information flow and resource sharing, thereby amplifying the network effects of virtual agglomeration. Conversely, in regions with weak infrastructure, its enabling role cannot be effectively realized, and its marginal contribution is constrained.

5.7. Endogeneity Tests

Given the potential bidirectional causal relationship between VA and NEVD, this study uses the total volume of postal and telecommunications services in each province in 1984 as an instrumental variable to test for endogeneity [77]. The current development of virtual agglomeration is closely linked to a region’s early telecommunications infrastructure; moreover, as a historical variable, it is unlikely to be directly influenced by current dynamics in the new energy vehicle industry, thereby satisfying the requirements for correlation and exogeneity of an instrumental variable.

Table 10 presents the results of the endogeneity test conducted using 2SLS. The first-stage regression results show that the coefficient of the instrumental variable (IV) is 1.044 and is highly significant at the 1% level, indicating a robust and statistically significant strong correlation between the instrumental variable and the endogenous variable of interest (VA). The Kleibergen–Paap rk LM statistic is 26.579 ($p = 0.000$), rejecting the null hypothesis of insufficient model identification. The Kleibergen–Paap rk Wald F statistic is 44.38, which is far greater than the critical value (16.38) for the Stock–Yogo weak identification test, confirming that there is no weak instrument problem. The coefficient of the VA in Stage 2 is 0.0542 and is significantly positive at the 5% level, which is consistent with the results of the baseline regression, indicating that the findings of this study are not driven by endogeneity bias.

Table 10. Endogeneity Test.

Variables	IV: First-Stage VA	IV: Second-Stage Nevd
IV	1.044 *** (0.157)	
VA		0.054 ** (0.027)
Constant	5.029 *** (0.840)	−0.932 *** (0.102)
Kleibergen–Paap rk LM statistic	26.58 ***	26.579 ***
Kleibergen–Paap rk Wald F statistic	44.38	44.378
Control variables	Yes	Yes
Obs	180	180

Notes: ** $p < 0.05$, *** $p < 0.01$.

6. Discussion

6.1. The Industrial Empowerment Effects of Virtual Agglomeration

Using provincial-level panel data from China as a sample, this study empirically examines the enabling effect of virtual agglomeration on the high-quality development of the new energy vehicle industry. The results indicate that virtual agglomeration has a stable and significant positive impact on the high-quality development of the new energy vehicle industry. After gradually introducing control variables, the coefficient remains statistically significant at the 1% level, and the core findings have passed multiple robustness tests. For a long time, traditional theories of industry agglomeration have emphasized that “geographical proximity” is a key factor in the generation of externalities, arguing that physical proximity facilitates the sharing of labor pools, the input of intermediate goods, and the spillover of tacit knowledge. However, with the increasing penetration of digital technology, “digital proximity” in the virtual space has gradually emerged as a new driving force for industry development. Romano et al. argue that virtual agglomeration can reshape the boundaries of economic activity [31], this study provides empirical evidence from the new energy vehicle industry. Furthermore, this demonstrates that virtual clusters formed through digital platforms and connectivity can effectively overcome geographical constraints, enabling cross-regional resource integration and collaborative innovation, and offering a new perspective on the coordinated development of strategic emerging industries across regions.

6.2. Mechanisms of Virtual Agglomeration

This study indicates that virtual agglomeration indirectly promotes the high-quality development of the new energy vehicle industry through two parallel pathways: boosting technology market activity and fostering collaborative innovation. The mediating effects of these two pathways account for 14.1% and 33.4%, respectively. In particular, the mediating role of technology market activity has expanded the application of technological market theory to the context of the digital economy, confirming that virtual agglomeration facilitates the cross-regional flow and commercialization of innovation outcomes by reducing information asymmetry and transaction costs. This finding aligns with the research conclusions of Kohtamäki et al. [33], who demonstrated that virtual agglomeration can significantly reduce transaction costs. Furthermore, compared to technology market activity, collaborative innovation pathways have demonstrated greater stability and stronger impact. This suggests that, for technology-intensive industries such as new energy vehicles, the core value of virtual agglomeration lies not only in reducing information asymmetry in factor markets, but also in establishing high-frequency R&D collaboration networks that facilitate the externalization of tacit knowledge and its cross-domain reorganization.

6.3. The Nonlinear Characteristics of Virtual Agglomeration Effects and the Moderating Role of the Regional Innovation Environment

This study further finds that the impact of virtual agglomeration on the development of the new energy vehicle industry is not linearly increasing. Tests for threshold effects revealed that virtual agglomeration exhibits a significant single-threshold effect. When the level of virtual agglomeration is below the threshold value, its coefficient of influence is 0.068 and is not statistically significant; however, once the threshold is crossed, the coefficient rises to 0.250 and becomes statistically significant at the 1% level. This finding challenges the assumption of a linear relationship commonly accepted in existing research, and the results are highly consistent with the theoretical predictions of Metcalfe's Law—namely, that network value grows with the square of the number of participants, and that network effects are fully realized only once the number of participants reaches a critical threshold.

In addition, the results of the moderation and heterogeneity analyses in this study also reveal the boundary conditions of the virtual agglomeration effect. The results indicate that the regional innovation environment plays a significant positive moderating role between virtual agglomeration and industry development; the coefficient of the interaction term between virtual agglomeration and the regional innovation environment is 0.360 and is significant at the 1% level; At the same time, the enabling effect of virtual agglomeration is only significant in regions with high levels of digital infrastructure following the implementation of the 2020 new infrastructure policy. These findings clearly demonstrate that the effectiveness of virtual agglomeration is highly dependent on the support of digital infrastructure and the complementary nature of the innovation ecosystem.

7. Recommendations and Research Limitations

7.1. Policy Recommendations

Considering the empirical results outlined above, this study puts forward the following targeted policy suggestions grounded in the practical needs and regional disparities of China's new energy vehicle industry development:

- (1) Implement differentiated and dynamic strategies for digital infrastructure development and virtual agglomeration advancement. Given that virtual agglomeration effects evolve over time and are influenced by policy, localities should formulate phased objectives and supportive measures for virtual agglomeration development in alignment with national policy strategies. In the initial phase, subsidies can be used to encourage enterprises to adopt cloud computing and utilize data. During the development phase, efforts should focus on promoting data openness and sharing, as well as building a cross-domain trusted collaboration environment. For regions with advanced digital infrastructure, further deepen the integration of new infrastructure like 5G and industrial internet with the new energy vehicle industry and support the development of cross-regional industry collaboration digital platforms. For regions with weak digital infrastructure, priority should be given to improving network coverage, enhancing bandwidth quality, and reducing data usage costs to lay the groundwork for virtual agglomeration.
- (2) Drive growth through the dual engines of revitalizing the technology market and strengthening collaborative innovation, while ensuring the smooth functioning of the virtual cluster mechanism. On the one hand, encourage government to collaborate with financial institutions and intellectual property agencies in establishing dedicated zones for new energy vehicle patents and technology transactions. Promote market-driven conversion models such as technology licensing, and enhance the vitality of the technology market through tax incentives. On the other hand, establish a special fund

- for collaborative R&D to support industry-academia-research partnerships, offer tax incentives and expedited patent review for cross-provincial joint patent applications, and build shared R&D infrastructure to enhance collaborative innovation efficiency.
- (3) Understand the patterns of nonlinear growth, optimize regional innovation ecosystems and implement targeted cultivation strategies. Prioritize support for key regions or leading enterprises with solid foundations in digitalization and clustering. Promote successful models through demonstration projects and benchmark parks to drive overall improvement. At the same time, assess the strengths and weaknesses of local R&D investment, patent output, and talent pools; in regions with strong innovation capabilities, facilitate the integration of platforms with local laboratories and pilot production facilities; and in regions with weak innovation foundations, increase R&D subsidies and establish public technology service platforms. Foster self-reinforcing mechanisms for virtual agglomeration, promote data standardization and the establishment of trustworthy collaboration rules, reduce participation costs, and facilitate the sustained and healthy development of the agglomeration ecosystem.

7.2. Research Limitations and Future Prospects

Despite its contributions, this study has several limitations that open avenues for future research. First, this study uses provincial-level data, which may obscure heterogeneity among cities or firms within a province. Future research could collect city-level or firm-level data to reveal the specific mechanisms through which virtual agglomeration affects new energy vehicle firms at the micro level. Second, although this study identifies two mediating pathways—technological market activity and collaborative innovation—the underlying mechanisms may be more complex. Future research could explore the mediating roles of additional pathways, such as digital engagement on the consumer side. Finally, as this study focuses on China's new energy vehicle industry, the generalizability of its findings to other industries or national contexts remains to be tested. Future research could conduct cross-industry comparative analyses and expand the scope to the transnational level. By utilizing transnational panel data, researchers could compare the differentiated impacts of virtual agglomeration on industrial development across varying levels of digital infrastructure, institutional environments, and cultural contexts, thereby testing the generalizability of this study's conclusions on a broader scale.

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Abbreviations

The following abbreviations are used in this manuscript:

VA	Virtual agglomeration
Nevd	High-quality development of the new energy vehicle industry

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