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The Impact of Industrial Structure Upgrading on Regional Coordination Development in the Digital Era: Evidence From China

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KEYWORDS

Industrial Structure Upgrading, Regional Development, Double Machine Learning

ABSTRACT

This paper investigates how industrial structure upgrading influences regional coordination in the digital era, using data from 253 Chinese prefecture-level cities between 2011 and 2021. The research employs a double machine learning model and constructs a Gini coefficient to quantify intracity disparities. Findings indicate that industrial structure upgrading reduces regional disparities overall, with stronger effects during the rapid digital economy development phase. However, in the initial phase of digital infrastructure construction, upgrading intensified disparities due to uneven access to resources and technologies. The analysis also reveals heterogeneity: cities with advanced industrial structures benefit from enhanced coordination, while those with underdeveloped structures face widened disparities. Digitalization moderates these effects by fostering innovation diffusion and improving resource distribution. This paper offers insights into how digitalization and industrial upgrading interact to influence regional coordination, providing a basis for tailored policies to achieve balanced and sustainable urban development.

1. Introduction

Since the reform and opening-up, China's economy has enjoyed rapid growth by fully capitalizing on demographic dividends and the benefits of market-oriented reforms (Wang and Wang, 2007). Leveraging its competitive advantage in labor-intensive industries, China quickly established a significant position in the international market. However, recent years have witnessed profound changes in the country's economic structure. Consumer demand continues to evolve, the composition of human capital is gradually adjusting, and production costs, including land and raw materials, are rising steadily. This has made the previous extensive growth model increasingly inadequate in meeting the demand for high-quality living standards. At the same time, widening regional and income disparities pose serious challenges to the sustainability of economic development (Zheng and Lu, 2019). Against this backdrop, coordinated region-

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al development has become a necessary approach to address issues of unbalanced and insufficient development and to overcome economic bottlenecks (Kong et al., 2022). Therefore, narrowing regional development gaps and promoting coordinated regional growth have become urgent priorities for advancing high-quality development.

Examining regional coordinated development further, numerous factors influence this process, as scholars have studied from various perspectives. (Li, 2019) explored the role of logistics industry development in enhancing regional interaction and balanced development, emphasizing that logistics serves as a foundation for regional economic connectivity. Li et al. (2020) found that equal access to for-profit public services is positively correlated with regional economic disparities, whereas equal access to non-profit public services effectively narrows these differences. Luo and He (2021) studied the impact of government intervention, finding that it positively influences developed provinces but may negatively affect less-developed ones. Qin (2021) observed that digital finance widened the economic gap between urban and rural areas in Shandong, indicating that digitalization's impact on regional development varies. Peng et al. (2021), using threshold and grouped regression models, found that as market integration advances, regional economic disparities initially widen but gradually converge. Zhong and Zheng (2021) demonstrated the spatial spillover effects of land finance policies in Zhejiang and Yunnan, which aid in interregional coordination. Additionally, Wang (2022) suggested that energy consumption patterns affect regional coordination differently, with economic zones outperforming developed regions in leveraging energy for economic growth. Wang et al. (2023) showed that the opening of the Shanghai-Kunming high-speed railway significantly enhanced accessibility and economic connections along its route, promoting regional coordinated development.

Despite extensive research into various factors influencing regional coordinated development, most existing studies predominantly focus on economic coordination at the provincial level or within urban clusters. These studies often overlook the specific impacts of industrial structure upgrading on intracity dynamics, particularly under the rapidly advancing digital economy. However, intracity disparities, such as the uneven distribution of resources and opportunities, remain critical barriers to achieving balanced regional development. Addressing these disparities requires a more granular perspective that considers the localized interactions between industrial upgrading and digitalization within prefecture-level cities.

As regional disparities continue to widen, the digital economy has emerged as a transformative force in reshaping urban and regional development. According to the 2024 China Digital Economy Development Research Report, digital penetration rates have reached 10.78%, 25.03%, and 45.63% in the primary, secondary, and tertiary sectors, respectively. This rapid expansion highlights the potential of digital technologies to mitigate traditional development bottlenecks by enhancing connectivity, reducing information asymmetry, and promoting innovation diffusion (Ji et al. 2022). However, the uneven distribution of digital infrastructure and access may also exacerbate existing disparities (Lythreatis et al. 2022), making it crucial to explore how digitalization interacts with industrial structure upgrading in promoting or hindering regional coordination.

In this context, this paper introduces three key points of innovation. First, it focuses on prefecture-level cities, offering a refined perspective that examines intracity dynamics rather than broader provincial or cluster-level analyses. Second, it explores the temporal heterogeneity of the relationship between industrial structure upgrading and regional coordination, analyzing how this impact evolves across different stages of digital economy development. By distinguishing between the initial phase of digital infrastructure construction and the subsequent rapid digitalization phase, this paper provides a nuanced understanding of how industrial upgrading interacts with varying levels of digital development to influence intracity disparities. Third, it highlights the moderating effect of digitalization, exploring how advancements in digital technologies shape the relationship between industrial structure upgrading and regional coordination, thereby providing deeper insights into regional coordination in the digital era.

By examining these dynamics, this paper aims to provide new perspectives for understanding how industrial structure upgrading, within the framework of digital economy development, can foster intracity and regional coordination. These findings are expected to inform policymaking on leveraging digital technologies and industrial upgrading to address regional disparities and promote sustainable and inclusive development in a rapidly digitalizing economy.

2. Theoretical Analysis

2.1. Industrial Structure Upgrading and Regional Coordination

With the rapid development of the digital economy, the emergence of high-value-added industries and the transformation of traditional enterprises have become key drivers of industrial structure upgrading (Chang et al. 2023). This process reallocates resources from low-value-added to high-value-added sectors, facilitating the integration of advanced technologies, skilled labor, and capital into core urban areas. By concentrating these resources, industrial structure upgrading creates the foundation for innovation-driven industrial clusters. Within these clusters, enterprises develop horizontal linkages, which involve collaboration and resource sharing among firms within the same industry, as well as vertical linkages, which connect upstream suppliers with downstream manufacturers to enhance supply chain efficiency. These interconnected relationships foster competition and cooperation, which together drive technological innovation and improve productivity (Fang and Liu 2024). Over time, the technological advancements and synergies generated by these clusters result in significant knowledge spillovers. These spillovers extend beyond core areas, reducing transaction and information acquisition costs for peripheral businesses and enabling their integration into high-value-added industries (Xu and Zhang 2024).

Industrial structure upgrading not only fosters innovation and productivity within core urban clusters but also transforms these clusters into growth poles, driving regional development through mechanisms described by growth pole theory. At the heart of this theory is the dynamic interplay between polarization effects and diffusion effects. Polarization effects dominate during the initial stages of growth pole formation, as leading industries rapidly attract economic activities and resources, creating concentrated hubs of innovation and economic activity. This resource aggregation enhances economies of scale, bolstering the growth pole's competitiveness and growth rate, yet also widening regional disparities.

As growth poles mature, however, rising operational and living costs reduce marginal productivity, triggering a shift toward diffusion effects. These effects facilitate the outward redistribution of production factors, industries, and economic opportunities to surrounding areas, integrating less-developed regions into broader economic and innovation networks. By narrowing regional disparities and promoting balanced development, diffusion effects ensure that the benefits of growth poles extend beyond core areas.

Industrial structure upgrading accelerates this process in two ways. First, it intensifies resource aggregation and innovation within core urban clusters, boosting their development. Second, it amplifies diffusion effects by enabling the relocation of high-value-added industries to peripheral regions. This dual role not only fosters the evolution of growth poles but also promotes the formation of polycentric urban structures, reducing intracity disparities and fostering coordinated regional growth (Liu et al. 2007).

In the context of the digital economy, industrial structure upgrading facilitates the relocation of high-value-added industries to non-core areas, driven by their lower dependence on geographic constraints. Emerging industries such as internet services, software development, and e-commerce often bypass core zones dominated by legacy industries due to high operational costs and spatial limitations. Instead, these industries find favorable conditions in peripheral regions, where land, labor, and logistics costs are lower, and opportunities for expansion are greater. This shift encourages the establishment of industrial parks and technology hubs in less-developed areas, transforming them into emerging economic centers (Liu 2009). The spatial redistribution of industries reduces congestion and resource strain in core areas while simultaneously driving economic growth in peripheral districts (Wang and Wen 2022). By fostering the development of a polycentric urban structure, industrial structure upgrading creates opportunities for underutilized regions to integrate into the broader urban economy, reducing intracity development disparities and promoting sustainable, coordinated urban growth.

Based on these theoretical insights, this paper proposes the first hypothesis:

Hypothesis 1: Industrial structure upgrading promotes regional coordination development.

2.2. Time-Segmented Heterogeneity

In the early stages of industrial structure upgrading, the distribution of digital infrastructure within cities often reflects significant disparities. Core areas, equipped with advanced digital facilities, skilled labor, and technological resources, dominate as the primary hubs of economic activity, where polarization effects are pronounced. These areas disproportionately benefit from industrial upgrading, leveraging their superior access to digital tools and established economic networks to attract additional resources and reinforce their competitive advantages (Guo et al. 2024). Conversely, peripheral areas, constrained by limited digital infrastructure and underdeveloped economic ecosystems, face significant barriers to integrating into high-value-added industries. This uneven distribution of resources and opportunities exacerbates development gaps, as peripheral regions struggle to participate fully in urban economic activities, widening disparities between core and non-core areas.

However, as digital infrastructure matures and its coverage expands to peripheral regions, the dynamics shift toward diffusion effects. Emerging industries which are less constrained by geographic dependencies begin to establish themselves in peripheral regions. Peripheral areas gain improved access to digital tools, enabling them to integrate into urban value chains and capitalize on industrial upgrading for productivity growth. This redistribution of digital resources facilitates the transfer of innovation, knowledge spillovers, and economic opportunities from core areas to less-developed regions, fostering their transformation into emerging economic centers. By promoting the formation of polycentric urban structures, the expanded reach of digital infrastructure helps alleviate resource strain in core areas, reduces regional disparities, and enhances urban spatial equity.

Based on these theoretical insights, this paper proposes the second hypothesis:

Hypothesis 2: The impact of industrial structure upgrading on regional coordination exhibits temporal heterogeneity.

2.3. Industrial Structure Heterogeneity

The level of initial industrial structure within cities significantly influences the outcomes of industrial upgrading. In cities with low industrial structure levels, traditional, labor-intensive industries dominate, and industrial upgrading often fails to achieve widespread benefits. High-value-added industries tend to cluster in core areas, concentrating resources and economic gains while leaving peripheral regions marginalized. These structural limitations, characterized by inadequate infrastructure, weak innovation capacity, and a lack of economic diversification, hinder the diffusion of benefits from industrial upgrading to less-developed regions.

In contrast, cities with advanced industrial structures are better equipped to foster balanced development. Their robust infrastructure, diversified economic base, and mature innovation ecosystems enable high-value-added industries, such as internet services and software development, to extend beyond core areas. Peripheral regions in these cities benefit from improved access to digital tools, knowledge spillovers, and supply chain integration, facilitating their transformation into emerging economic centers. This spatial redistribution promotes the formation of polycentric urban structures, where diverse and interconnected economic nodes enhance collaboration and reduce intracity disparities. By optimizing the spatial layout of industries, cities with advanced industrial structures leverage industrial upgrading to promote equitable growth, integrate less-developed regions into urban economic networks, and foster sustainable and coordinated urban development.

Based on these insights, this paper proposes the third hypothesis:

Hypothesis 3: The impact of industrial structure upgrading on regional coordination exhibits heterogeneity based on the level of industrial structure within cities.

2.4. Digitalization Level, Industrial Structure Upgrading, and Regional Coordination

Digitalization acts as a facilitator by providing the essential infrastructure that amplifies the effectiveness of industrial upgrading. Enhanced digital networks improve connectivity across urban regions, breaking down traditional barriers to communication, collaboration, and resource allocation. By reducing transaction costs and bridging geographic divides, digitalization integrates peripheral areas into broader economic networks (Yuan and Zhu 2023). This interconnectedness allows peripheral regions to adopt advanced production methods, participate in high-value-added supply chains, and access broader markets that were previously exclusive to core areas. By fostering stronger economic linkages, digitalization contributes to the redistribution of industries and resources, supporting the emergence of multiple economic centers. This spatial restructuring alleviates resource strain in core regions and provides new growth opportunities for peripheral areas, promoting a balanced urban development framework where the benefits of industrial upgrading are distributed more equitably.

Furthermore, digitalization accelerates the diffusion of innovation and knowledge, critical drivers of industrial upgrading. Digital platforms enhance resource allocation by matching labor, capital, and technological expertise with the regions that need them most, optimizing urban productivity. These platforms also enable businesses in less-developed areas to access global best practices, advanced tools, and real-time data, enhancing their competitiveness in knowledge-driven industries (Qi and Xiao 2020). The improved accessibility facilitated by digital tools narrows the innovation and productivity gaps between core and peripheral regions, aligning their development trajectories. Over time, these mechanisms foster the integration of peripheral regions into urban economic networks, reducing disparities and reinforcing coordinated urban growth.

Based on these considerations, this paper proposes the fourth hypothesis:

Hypothesis 4: Digitalization positively moderates the impact of industrial structure upgrading on regional coordination development.

3. Research Design

3.1. Data Selection

3.1.1. Explained Variable

Regional coordinated development, as defined by scholars, involves not only reducing economic disparities but also addressing gaps in social dimensions, such as residents' living standards and overall quality of life (Williamson 1965; Gruhn 1971). While economic coordination refers to the convergence of income levels, wealth distribution, and access to resources, social coordination focuses on ensuring that all urban areas provide equitable access to essential services, healthcare, education, and other factors that contribute to a good quality of life. Nighttime light data, which is widely used to reflect economic activity, also serves as an effective proxy for social development, as brighter areas are typically associated with higher levels of both economic growth and the availability of social amenities (Elvidge et al. 2012; Yun et al. 2024). Given its ability to capture both economic and social disparities, this paper uses the Gini coefficient derived from DMSP-OLS-like nighttime light data (Wu et al. 2021) to assess intracity coordinated development. A higher Gini coefficient suggests significant imbalances in both economic and social development across different urban areas, while a lower Gini coefficient indicates a more balanced distribution of resources, reflecting a city's progress toward equitable growth in both economic and social dimensions. The specific calculation method for the Gini coefficient is shown in Equation (1):

$$Gini_{it} = \frac{\sum_{k=1}^{n_i} \sum_{r=1}^{n_i} \left| L_{ikt} - L_{irt} \right|}{2n_i^2 \overline{L_{it}}} \tag{1}$$

In this formula, n_i denotes the total number of urban and township areas within the i-th prefecture-level city. $\overline{L_{it}}$ represents the average nighttime light intensity for the i-th city in year t. L_{ikt} represents the nighttime light intensity for the r-th urban or township area in city i during year t. L_{irt} denotes the nighttime light intensity for the r-th urban or township area within a city at or above the prefecture level i during year t. A larger Gini represents a larger development gap within the city, which is less beneficial to the coordinated development of the region.

3.1.2. Explanatory Variable

The Petty-Clark Law suggests that as an economy develops, labor and resources gradually shift from the low-value-added primary sector to the secondary and tertiary sectors, leading to an optimized economic structure. Based on this theory, this study adopts the overall industrial structure upgrading index (UIL), as in Yu and Wang (2021), to evaluate industrial structure advancement. The calculation formula for UIL is shown in Equation (2), where P_{ikt} represents the proportion of the added value of the k-th industry in the i-th prefecture level city's GDP in year t. A higher UIL value indicates a more advanced industrial structure in the prefecture-level city.

$$UIL_{it} = \sum_{k=1}^{3} P_{ikt} \cdot k \tag{2}$$

3.1.3. Moderator Variable

To further explore the moderating effect of digitalization on the relationship between industrial structure upgrading and regional coordination, this paper employs the Digital Inclusive Finance Index (Guo et al. 2020) as a measure of the degree of digitalization. The index captures multiple dimensions of digital finance penetration, including coverage, usage, and depth, making it a comprehensive indicator for assessing regional digitalization levels. This choice ensures that the selected variable captures the nuanced impact of digitalization, providing a robust foundation for the subsequent analysis.

3.1.4. Control Variables

To ensure the validity of the estimation results, this paper sets control variables based on relevant literature and data availability as follows:

1) Economic Development Level: According to Lucas (1988), urban core areas, with higher concentrations of human capital, are more likely to benefit from technological advancements and improved productivity, thus reaping greater rewards from economic growth. In contrast, peripheral and less-developed areas, lacking sufficient human capital, struggle to achieve the same advantages, thereby widening economic disparities within cities. To measure the level of economic development, this paper uses the logarithm of per capita GDP (GDP).
2) Financial Development Level: Financial development provides sufficient capital support citywide, facilitating financing opportunities for enterprises across districts, especially small and medium-sized enterprises, by improving access to loans. This increased capital flow helps relatively underdeveloped areas foster industry growth, creating employment opportunities, reducing regional development disparities, and promoting coordinated regional development (Bu 2024). Therefore, the logarithm of year-end loan and deposit balances of financial institutions (DL) is selected as an indicator of financial development level.
3) Education Level: Investment in education raises overall human capital, promoting technological progress, reducing transaction costs, and lowering regional development disparities, thus facilitating regional coordination (Guan et al. 2019; Hu and Yao 2023). To measure education levels, this paper uses the logarithm of the number of enrolled university students (SN) and the logarithm of educational expenditure (EI)
4) Technological Development Level: Technological innovation can enhance the free exchange and flow of capital, talent, and technology within and between regions, generating spillover effects of technological progress on neighboring areas, thereby fostering regional coordination (Chen and Cai 2023). For this reason, the logarithm of government science expenditures (ES) is chosen as an indicator of technological development level.

To further control for missing information in the city and time dimensions, this paper incorporates city and year fixed effects using individual and year dummy variables.

3.1.5. Data Source

Considering data availability, this paper conducts an empirical study on 253 prefecture-level cities in China from 2011 to 2021. The primary data sources include the China City Statistical Yearbook, statistical yearbooks of various provinces and cities, and the statistical bulletins on national economic and social

Table 1 | Descriptive statistics

Type	Variable	Obs	Mean	Std.	Min	Max
Explained variable	Gini	2783	0.407	0.147	0.016	0.792
Explanatory variable	UIL	2783	2.309	0.142	1.900	2.836
Control variable	EI	2783	13.032	0.981	8.424	16.256
	SN	2783	10.723	1.276	6.640	14.161
	ES	2783	10.569	1.413	6.624	15.529
	DL	2783	17.543	1.104	15.079	21.746
	GDP	2783	10.768	0.566	8.773	12.456
Moderator variable	DIFI	2783	185.837	73.191	21.260	359.683

development. Table 1 presents the descriptive statistics for the variables used in this paper.

3.2. Empirical Model Setting

Previous studies on regional coordinated development have often employed the Ordinary Least Squares (OLS) regression model. However, in high-dimensional data and multi-variable control environments, the OLS model is susceptible to multicollinearity and the curse of dimensionality, limiting its ability to estimate causal effects accurately. Specifically, when research involves numerous control variables or potential confounders, the OLS model may encounter two main challenges: first, multicollinearity, where high correlations among variables lead to unstable parameter estimates, thus introducing bias in causal inference; second, the curse of dimensionality, as increased data dimensions lead to insufficient sample size or data sparsity, making it difficult for OLS to effectively control confounding factors in high-dimensional settings. Additionally, OLS relies on a parametric specification of the functional form between control variables and the dependent variable, making it prone to bias if the functional relationship is misspecified. These limitations present a risk of significant model specification bias when applying OLS to complex economic data.

To address these challenges, this paper employs the Double Machine Learning (DML) model, which is particularly suitable for analyzing causal relationships in high-dimensional, multi-variable control environments. DML effectively addresses three key issues that limit traditional OLS in this context. First, it mitigates multicollinearity by using machine learning algorithms to automatically select the most relevant explanatory variables while suppressing the influence of irrelevant or weakly related variables. This ensures stable and unbiased parameter estimates, even when high correlations exist among variables. Second, DML overcomes the curse of dimensionality by leveraging a double estimation procedure with cross-fitting techniques, which enhances robustness and prevents overfitting, enabling accurate causal inference despite the complexity and sparsity of high-dimensional data. Finally, DML adopts a nonparametric approach to estimate the relationship between control variables and the dependent variable, avoiding the need to predefine the functional form. This flexibility ensures that the model captures complex and potentially non-linear relationships, reducing biases caused by misspecified functional forms (Yang et al. 2020).

For this paper, where analyzing the effects of industrial structure upgrading on regional coordination involves numerous control variables and complex interactions, DML's capability to handle multicollinearity, high-dimensional data, and the flexible treatment of control variables ensures stable and reliable results. This paper, therefore, adopts a partially linear model based on Chernozhukov et al. (2018), as shown below.

$$Gini_{it} = \theta_0 UIL_{it} + g\left(X_{it}\right) + \epsilon \quad E[\epsilon \mid X_{it}] = 0 \tag{3}$$

$$UIL_{it} = f\left(X_{it}\right) + \phi \quad E[\phi \mid X_{it}] = 0 \tag{4}$$

$$E[\epsilon \cdot \phi \mid X_{it}] = 0 \tag{5}$$

In this formula, i denotes the prefecture-level city, t denotes the year, $Gini$ represents the degree of urban internal regional development disparity, UIL represents the level of industrial structure upgrading, θ_0 is the coefficient of industrial structure upgrading level, X_{it} represents high-dimensional control variables, $g\left(X_{it}\right)$ and $f\left(X_{it}\right)$ are non-parametric functions, and ϵ and φ are error terms.

The non-parametric parts are fitted using machine learning algorithms, and residuals are calculated as shown in Equations (6) and (7).

$$\widetilde{Gini}_{it} = Gini_{it} - g\left(X_{it}\right) \tag{6}$$

$$\widetilde{UIL}_{it} = UIL_{it} - f\left(X_{it}\right) = \phi \tag{7}$$

The residuals are then linearly fitted using ordinary least squares as shown in Equation (8) to calculate θ_0.

$$\widetilde{Gini}_{it} = \theta_0 \widetilde{UIL}_{it} + \epsilon \tag{8}$$

4. Empirical Results and Analysis

4.1. Benchmark Regression Analysis

This paper employs DML to estimate the effects of industrial structure upgrading on regional coordination development, using the Gradient Boosting Decision Tree algorithm for the nonparametric component and a 1:4 sample-splitting ratio. The results in Table 2 show that, in Column (1), the coefficient for industrial structure upgrading is -0.262 and statistically significant at the 1% level, indicating that industrial upgrading significantly reduces regional disparities. After incorporating control variables in Column (2), the coefficient decreases to -0.099 but remains significant at the 1% level, demonstrating the robustness of the results while accounting for additional confounding factors. This result validates Hypothesis 1, confirming that industrial structure upgrading promotes regional coordination development.

4.2. Robustness Analysis

4.2.1. Resetting the Double Machine Learning Model

In order to verify the robustness of the conclusions, the machine learning model was reset in this paper and the results are shown in Table 3. In Column (1), where the sample-splitting ratio is adjusted to 1:5, the coefficient of UIL remains negative and statistically significant at the 1% level. Similarly, in Column (2), when the Gradient Boosting Decision Tree algorithm is replaced with extreme gradient boosting (XGBoost), the coefficient of UIL is -0.060 and significant at the 5% level. These consistent results, regardless of changes in sample-splitting ratios or machine learning algorithms, confirm the robustness of the findings, further validating Hypothesis 1 and reinforcing the conclusion that industrial structure upgrading promotes regional coordination development.

4.2.2. Excluding Outliers

To address the potential bias caused by outliers in the regression sample, this paper applies winsorization to all variables in the benchmark regression, winsorizing extreme values at the 1% and 99% percentiles as well as the 5% and 95% percentiles. In these cases, values above the highest percentile and below the lowest percentile are replaced accordingly. The results of the regression analyses are shown in Columns (1) and (2) of Table 4. It can be observed that, even after eliminating the influence of outliers, the conclusions of this paper remain consistent, with UIL coefficients of -0.107 and -0.124, both statistically significant at the 1% level.

Furthermore, given the administrative and economic differences between municipalities and prefecture-level cities, municipalities often possess greater resource concentration capacities, policy advantages, and more developed infrastructure, which may result in economic development patterns distinct from those of ordinary cities. To ensure robustness, municipalities were excluded from the regression analysis, and the results are presented in Column (3) of Table 4. The UIL coefficient remains statistically significant at the 1% level, demonstrating that the exclusion of municipalities does not materially alter the findings. These analyses confirm the robustness of the regression results, supporting the conclusion that industrial structure upgrading significantly promotes regional coordination development.

4.2.3. Exclusion of Other Relevant Policies

To ensure the robustness of the analysis and eliminate the potential interference of other policy factors, this study incorporates resource-based cities identified in the National Sustainable Development Plan for Resource-based Cities (2013–2020) as a control variable. Specifically, dummy variables were generated for the cities listed in the plan and included in the regression model. This adjustment is crucial because resource-based cities may have received targeted policy support during the plan's implementation peri-

Table 2 | Benchmark regression results

	(1)	(2)
UIL	-0.262*** (0.029)	-0.099*** (0.035)
Control variables	No	Yes
Fixed effect	Yes	Yes
Sample size	2783	2783

Notes: Robust standard errors are in parentheses. *, **and *** denote significance at 10%, 5% and 1% levels.

Table 3 | Estimation results of resetting DML model

	(1)	(2)
UIL	-0.097*** (0.036)	-0.06** (0.027)
Control variables	Yes	Yes
Fixed effect	Yes	Yes
Sample size	2783	2783

Notes: Robust standard errors are in parentheses. *, **and *** denote significance at 10%, 5% and 1% levels.

od, which could directly or indirectly influence intraregional coordination development. As shown in Column (4) of Table 4, the coefficient of UIL is -0.074, which is significant at the 5% level, confirming the robustness of the regression results.

4.3. Heterogeneity Analysis

4.3.1. Heterogeneity Analysis of Time Dimension

In alignment with China's evolving development policies in the digital economy, this paper segments the timeline to analyze the temporal heterogeneity in the impact of industrial structure upgrading on urban regional coordination. The timeline is divided based on two significant policy milestones that shaped the digital economy's trajectory. In 2011, the Twelfth Five-Year Plan for National Economic and Social Development highlighted the acceleration of information infrastructure construction as a critical component of economic modernization. This period prioritized expanding network coverage and improving the digital infrastructure layout, laying the groundwork for industrial transformation. In 2016, the adoption of the G20 Digital Economy Development and Cooperation Initiative elevated the digital economy to a national strategic priority. This shift marked the transition to a phase of rapid digital economy development, characterized by widespread adoption of digital technologies and their

Integration into economic activities. Accordingly, this study defines 2011-2015 as the Digital Infrastructure Construction Period and 2016-2021 as the Digital Economy Rapid Development Period.

The results in Column (1) of Table 5 provide empirical evidence of temporal heterogeneity during the Digital Infrastructure Construction Period. The coefficient of UIL is 0.156 and statistically significant at the 1% level. This positive coefficient suggests that industrial structure upgrading exacerbated intracity development disparities during this phase. Core urban areas, benefiting from prioritized infrastructure investments, concentrated resources, and access to emerging technologies, disproportionately captured the gains from industrial upgrading. Conversely, peripheral regions, constrained by insufficient digital infrastructure and weak technological capacity, struggled to integrate into high-value-added industries. These structural limitations amplified disparities, reflecting the dominance of polarization effects in this early stage. The uneven distribution of digital infrastructure and resources during the Digital Infrastructure Construction Period hindered the spatial diffusion of economic opportunities, underscoring the challenges associated with the initial stages of digital economic development and the structural barriers faced by less-developed areas.

In contrast, Column (2) of Table 5 highlights a significant shift during the Digital Economy Rapid Development Period. The coefficient of UIL is -0.133 and statistically significant at the 1% level, indicating that industrial structure upgrading reduced intracity development disparities in this phase. As digital infrastructure became more evenly distributed across urban areas, peripheral regions gained improved access to digital tools, resources, and innovation networks. At this stage, diffusion effects and spillover effects began to dominate, enabling the transfer of innovation, technological advancements, and economic opportunities from core areas to peripheral regions. Emerging industries, characterized by lower

Table 4 | Estimation results of excluding outliers and other relevant policies

	(1)	(2)	(3)	(4)
UIL	-0.107^{***} (0.035)	-0.124^{***} (0.033)	-0.095^{***} (0.034)	-0.074^{**} (0.035)
Control variables	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
Sample size	2783	2783	2739	2789

Notes: Robust standard errors are in parentheses. *, **and *** denote significance at 10%, 5% and 1% levels.

geographic dependency, established themselves in peripheral regions, transforming these areas into dynamic economic centers. This redistribution of resources not only alleviated resource strain in core areas but also facilitated the formation of polycentric urban structures. The dominance of diffusion and spillover effects during this phase played a pivotal role in enhancing urban spatial equity, reducing regional disparities, and fostering balanced regional development. The transition from negative effects to positive effects during this phase validates Hypothesis 2, demonstrating that the impact of industrial structure upgrading on regional coordination evolves over time, driven by infrastructure development.

4.3.2. Heterogeneity Analysis of Industrial Structure

Based on the median value of industrial structure upgrading, this paper segments cities into high and low industrial structure upgrading groups and conducts separate regression analyses for each group.

In the high industrial structure upgrading group, as shown in Table 5 Column (3), the coefficient for UIL is -0.182 and statistically significant at the 1% level. This negative coefficient indicates that industrial upgrading significantly reduces intracity development disparities in cities with advanced industrial structures. These cities, equipped with well-developed infrastructure, skilled labor, and robust innovation ecosystems, create favorable conditions for the diffusion of resources and economic opportunities beyond core areas. Mechanisms such as knowledge spillovers, supply chain integration, and the redistribution of high-value-added industries allow peripheral regions to transform into emerging economic centers. These findings validate that advanced industrial structures enable cities to leverage industrial upgrading for balanced urban growth and coordinated regional development.

Conversely, in the low industrial structure upgrading group, as shown in Table 5 Column (4), the coefficient for UIL is 0.155 and statistically significant at the 5% level. This positive coefficient suggests that industrial upgrading increases intracity development disparities in cities with less-developed industrial structures. These cities, characterized by reliance on traditional, labor-intensive industries and limited innovation capacities, concentrate resources and benefits in core areas while marginalizing peripheral regions. Structural limitations, such as inadequate infrastructure and weak economic diversification, hinder the diffusion of economic opportunities, resulting in a pronounced polarization effect. Peripheral regions in these cities are excluded from the gains of industrial upgrading, widening disparities and exacerbating regional imbalances. These results demonstrate that cities with less-developed industrial structures face significant challenges in integrating peripheral regions into urban economic systems, limiting their potential for coordinated development. These results validate Hypothesis 3, demonstrating that the effects of industrial structure upgrading on regional coordination exhibit clear heterogeneity based on the initial levels of industrial structure within cities.

4.4. Mechanism Analysis

To further explore the moderating effect of digitalization on the relationship between industrial structure upgrading and regional coordination, this paper conducts a moderation effect analysis. To address potential multicollinearity, the interaction term is constructed by mean-centering both the industrial structure upgrading variable and the digitalization variable. The results are shown in Column (1) of Table 6. The

Table 5 | Heterogeneity analysis results

	(1)	(2)	(3)	(4)
UIL	0.156*** (0.055)	-0.133*** (0.043)	-0.182*** (0.058)	0.155** (0.065)
Control variables	Yes	Yes	Yes	Yes
Fixed effect	Yes	Yes	Yes	Yes
Sample size	1265	1518	1393	1390

Notes: Robust standard errors are in parentheses. *, **and *** denote significance at 10%, 5% and 1% levels.

coefficient of the interaction term is -0.002, statistically significant at the 5% level. This indicates that digitalization significantly enhances the positive impact of industrial structure upgrading on regional coordination. However, the relatively small coefficient reflects the large range and variance of the digitalization variable, which may lead to an underestimation of the moderating effect despite its statistical significance.

To address this issue, the digitalization variable is normalized, and the interaction term is reconstructed. The results for the normalized digitalization variable are shown in Column (2) of Table 6. After normalization, the interaction term's coefficient increases to -0.565 and remains statistically significant at the 5% level. This stronger coefficient underscores the substantial moderating role of digitalization, suggesting that its effect on the relationship between industrial structure upgrading and regional coordination is more pronounced than initially indicated.

These findings validate Hypothesis 4, demonstrating that digitalization acts as a critical enabler in amplifying the benefits of industrial structure upgrading for regional coordination. By reducing transaction costs, enhancing resource allocation, and bridging geographic divides, digitalization facilitates the integration of peripheral regions into broader economic networks. Furthermore, digital platforms foster innovation diffusion and knowledge sharing, empowering less-developed areas to adopt advanced production methods and participate in high-value-added supply chains. This interconnectedness contributes to the redistribution of industries and resources, supporting the formation of polycentric urban structures and reducing intracity disparities. Over time, these mechanisms promote inclusive growth, balance resource allocation across regions, and advance the sustainable development of urban economies.

5. Conclusion and Policy Enlightenment

This paper examines the impact of industrial structure upgrading on regional coordination in Chinese cities within the context of the digital economy. By constructing a Gini coefficient to measure regional coordination within cities and employing a double machine learning model, the research analyzes the mechanisms and heterogeneous effects of industrial structure upgrading on regional disparities. The findings reveal that industrial structure upgrading significantly reduces regional disparities, with this effect being more pronounced during the rapid development phase of the digital economy. However, during the initial phase of digital infrastructure construction, industrial structure upgrading exacerbated regional disparities. Additionally, the impact of industrial structure upgrading on regional coordination exhibits significant heterogeneity: cities with advanced industrial structures are better able to achieve broad resource sharing and coordinated development, while cities with less developed industrial structures experience greater resource concentration in core areas, further widening disparities. Mechanism analysis shows that digitalization significantly enhances the positive moderating effect of industrial structure upgrading on regional coordination by promoting innovation diffusion and balanced distribution of economic resources.

Based on the findings of this paper, several policy insights for promoting intracity regional coordination

Table 6 | Estimation results of mechanism analysis

	(1)	(2)
UIL	-0.137*** (0.049)	-0.139*** (0.049)
DIFI*UIL	-0.002** (0.001)	-0.565** (0.252)
DIFI	-0.002*** (0.001)	-0.509*** (0.069)
Control variables	Yes	Yes
Fixed effect	Yes	Yes
Sample size	2783	2783

are proposed. Firstly, industrial structure upgrading should be accelerated by integrating policy guidance with market mechanisms to promote the technological transformation of traditional industries and the development of emerging industries. The government should provide low-interest loans to support enterprises in technological transformation, equipment renewal, and intelligent upgrades, alleviating the financial pressure during the transition process. Additionally, efforts should be made to establish technology transfer centers or platforms to help traditional enterprises access technological resources from universities and research institutions, thereby facilitating the application of innovative outcomes. Strengthening support for high-value-added industries, optimizing resource allocation, and encouraging enterprises to move up the value chain are also crucial. On this basis, efforts should be made to enhance resource and technological spillovers between core and peripheral regions, fostering resource sharing through collaborative mechanisms and narrowing regional disparities.

Secondly, digital infrastructure construction should be improved, and the pace of digital transformation should be accelerated. The development of digitalization can significantly enhance the positive impact of industrial structure upgrading on regional coordination. Therefore, digital infrastructure construction should be prioritized, especially in areas with weak foundations, to improve network coverage and the accessibility of digital tools by advancing 5G networks, high-speed broadband, and data centers. Efforts should also focus on promoting integrated digital platforms such as industrial internet, smart cities, and digital villages to facilitate the deep integration of traditional industries with digital technologies. Additionally, investment in digital skills training for enterprises and workers should be increased, along with encouraging research institutions to drive innovation in cutting-edge fields like artificial intelligence and blockchain.

Finally, differentiated support policies should be formulated based on the level of industrial structure and digital infrastructure development in each region. For regions with lower levels of industrial structure upgrading, priority should be given to enhancing basic infrastructure capabilities and increasing fiscal and technical support to help them better integrate into high-value-added industrial chains. For regions with higher levels of industrial structure upgrading, efforts should focus on improving innovation capacity, optimizing resource diffusion mechanisms, and leveraging technological spillovers and collaborative development to drive neighboring areas. Promoting coordination based on comparative advantages in different regions through targeted policies and positive regional interactions can ensure the efficient allocation of urban resources and foster higher-quality regional coordination development.

These policy insights provide a theoretical foundation and practical pathway for enhancing regional coordination under the digital economy. Through well-designed policies and effective implementation, industrial structure upgrading can drive regional coordination, laying the foundation for high-quality, sustainable urban economic development.

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