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# Digital Economy-Driven Coordinated Industrial and Ecological Transformation: Mechanisms and Effects, Empirical Evidence from Northern Anhui within the Yangtze River Delta

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**SUMMARY:** *The article analyzes the contribution of the digital economy to the coordinated changes of industries and environment in Northern Anhui as part of the Yangtze River Delta. Through a balanced panel of 41 prefecture cities during 2011-2020 ($N = 410$), we construct a coordinated transformation index (CTI) of an industrial subsystem (structural advancement, rationalization, labour productivity, innovation capability, and digital integration) and an ecological subsystem (pollution intensity, resource pressure, environmental governance, and green coverage) through the entropy-weighting methodology. The Digital Financial Inclusion Index developed by Peking University is utilized as the proxy of the city level digital economy. The two-way fixed-effects model results in $\beta = 0.087$ ($p < 0.01$), indicating that it has a statistically significant positive effect on the CTI. Mechanism tests indicate three mediated pathways: industrial restructuring (the direct effect was decreased to 0.069), green innovation (decreased to 0.072), and resource allocation efficiency (decreased to 0.073). The heterogeneity analysis reveals higher heterogeneity in Northern Anhui ($\beta=0.118$) than in other Yangtze River Delta cities ($\beta=0.081$). It is also supported by a Spatial Durbin Model, which has both direct effect of 0.088 and a spillover effect of 0.052, which confirms cross-city complementarities. The results are similar to other proxies, lagged specifications and sample limitations. The online development serves as a structure integrator that can enhance both industrial and ecological performance simultaneously.*

***KEYWORDS:*** *Digital economy; coordinated transformation; ecological transition; Northern Anhui; Yangtze River Delta*

## 1 Introduction

The digital economy will be the determining structural element in the evolution of regions. By 2023, the national digital economy in China has reached RMB 53.9 trillion (or 42.8% of GDP), which has made digitization a major contributor of structural change. Nevertheless, general statistics conceal significant spatial discrepancies: some cities use the digital revolution as a source of productivity-driven growth and others simultaneously face industrial restructuring, environmental degradation.

Such a dualism is clearly visible in both the Yangtze River Delta (YRD). As of 2021, YRD regional GDP stood at RMB 27.6 trillion or some 34.1 % of the national total with the regional digital economy estimated to represent no more than 28 percent of the national digital economy aggregate. [2] Still, such resources are not distributed equally. North Anhui, which comprises

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Fuyang, Bozhou, Suzhou, Bengbu, Huainan and Huaibei, is a sub-region of strategic importance, however, it is also a late transformer. Compared with coastal and core YRD cities, Northern Anhui has a greater weight in terms of industrial legacy, more severe ecological pressure per unit of economic output, and weaker digital absorption capabilities. The main research question that drives this paper is whether the digital economy is able to act as a synchronized catalyst of industrial upgrading and ecological preservation in this environment.

The previous studies have found relationships regarding digitalization and industrial restructuring, green innovation, eco-efficiency, and the performance of carbon emissions.[3, 4, 5, 6] There are three critical gaps. Firstly, industrial change and ecological change have been usually considered as disjoint effects, which does not allow evaluating their concerted evolution. Secondly, subregional differentiation in integrated agglomerations such as the YRD is seldom directly addressed. Third, transmission mechanisms are often considered individually, so that they cannot be compared with respect to their relative contribution within a single framework.

The paper deals with all these three gaps through building a coordinated transformation index (CTI) based on both industrial and ecological subsystems, measuring the impact of the digital economy on this combined result of the 41 YRD cities during 2011-2020, and specifying three simultaneous transmission mechanisms including industrial restructuring, green innovation, and the efficiency of resource allocation. The main heterogeneity group in the entire 41-city panel is Northern Anhui. There are three contributions: a unified empirical framework of coordinated industrial-ecological transformation; simultaneous estimation of three mechanism channels and comparison of their relative sizes; and formal positioning of Northern Anhui in the YRD structural dynamics.

# 2 Literature Review

## 2.1 Digitalization, industrial transformation, and ecological transition

The study of the economic implications of digitalization has evolved into two interrelated but not fully integrated lines. The first relates to industrial transformation. Digital tools reduce transaction costs, enhance information flow, promote supply chain coordination and increase market connectivity, allowing reallocation of capital, labor and managerial capacity to more productive and high value industries. Research on the 41-city cluster of the YRD confirms that digital development contributes to the industrial structure advancement especially due to the servitization of advanced manufacturing.[5] The provincial data also indicates that development of the digital economy is strongly associated with a significant decrease in the intensity of carbon emissions owing to the changes in the industrial structure.[7]

The next line discusses the digitalization in the context of ecological transformation. At city level, digital economy development is associated with lower carbon emission intensity [7], urban eco-efficiency improvement, and better green technological innovation when digital finance loosens the constraints on innovation financing [9]. The spatial econometric literature reports the existence of positive spillovers of the digital finance on green patent activities between Chinese cities [10]. The digital economy has a positive effect on low-carbon innovation and this effect is stronger in non-central cities according to the YRD cross-city analysis [6].

Although there is a lot of information about each of the dimensions, the two lines are poorly integrated, and it is not possible to assess whether digitalization leads to their synchronized co-evolution, which is the main issue discussed in this paper.

### 2.2 Coordinated industrial-ecological transformation: measurement

Coordination of industrial-ecological transformation refers to a developmental process whereby industrial modernization and ecological improvement progress in mutually supporting directions. Green total factor productivity, which measures overall environmental- economic performance but cannot isolate structural changes versus efficiency improvements, is an existing measurement strategy as are coupling-coordination degree models that produce intuitive joint-evolution summaries that may hide the composition of each subsystem within them, and subsystem-based composite indices that make the reasoning behind both subsystems and their combination clear and explicit. [10] The system of subsystems is the most analytically feasible regression analysis since it yields a continuously measured and uniformly scaled outcome variable, and it enables decomposition into industrial and ecological factors. Indicator weights are determined by entropy-weighting using variability of information among observations, eliminating any arbitrary subjective weighting.[11]

### 2.3 Transmission mechanisms

According to the mechanism literature, there are three mechanisms through which digitalization can impact coordinated transformation. The first one is Industrial restructuring. Digitalized tools lower adjustment costs and enhance market opportunity information, which enables movement into more sophisticated and less resource-demanding sectors. Ecological pressure has a tendency to decrease as industrial composition increases since high-value activities tend to be cleaner and able to implement green technologies. Green innovation is the second way. Information asymmetry and financing frictions of green-technology investments are easier with digital platforms and digital finance.[9, 12] The channel is important to the coordinated transformation because improving ecology takes more than regulatory compliance, it relies upon increasing the limits of industrial activity that is ecologically friendly. Efficiency in resource allocation is the third channel. Digital systems reduce search and matching expenses, enhance factor migration and increase inter-city connections. Studies indicate that the efficiency of labor allocation between sectors significantly increases with the development of the digital economy.[13]

### 2.4 Research gaps

The study is inspired by three gaps. The first one is that there is no extant city-level research that assesses coordinated industrial-ecological transformation as an overall result and evaluates the impact of the digital economy on it directly. Secondly, the status of Northern Anhui as a unique heterogeneity group of the digital economy in YRD has not yet been officially tested. Third, the role played by industrial restructuring, green innovation, and resource allocation efficiency as concurrent transmission channels in the YRD setting have not been defined. All three are discussed in this paper.

## 3 Theoretical Framework and Hypotheses

The conceptual framework starts with the idea that the digital economy is a systemic reorganization of the way regional economies handle information, coordinate production, incorporate markets, and react to constraints, such as ecological ones. At a certain level of depth and breadth of digital development in a region, it changes the incentive environment of companies, the cost structure of structural adjustment, and the governance potential of institutions. These changes do not only act within cities in an integrated urban agglomeration, but also between them via common digital infrastructure, intercity market connectivity, and factor mobility facilitated by digital coordination systems.

One of the outcomes of this systematic approach is the ability of digitization to affect different elements of regional performance. Assuming that digitalization offers higher information content to business decision-making processes, reduces the cost of green innovation, and increases the effectiveness of resource allocation, both the quality of the industrial sector and its ecological performance may be enhanced concurrently rather than sequentially. This kind of synchronized dynamism is qualitatively different to a context where digitalization can help increase industrial production at the expense of ecological degradation, or it can assist ecological compliance at the expense of industrial economic stagnation. This idea of coordinated change perfectly conveys this opportunity; it asks if digitalization can be used as a structural integrator that takes both industry and ecology in mutually supporting directions.

Digital technologies are also integrated into the social fabric of production and governance which produces feedback mechanisms, which improve coordination over time. As the industrial structure continues to develop, the requirement of digital services by companies also rises, and this drives the level of digital penetration even higher and also contributes to restructuring. Eco-governance development through digital monitoring and reporting will expand the size of green technology markets to boost green innovation itself which is digitally supported. Such feedback effects suggest that the effect of the digital economy on coordinated change cannot merely be additive, but may be self-perpetuating such that early investments in digital capability might have especially high stakes regarding where the development trajectory of a later transforming sub-region like Northern Anhui heads in the future.

Concerning the direct effect, the digital infrastructure will enlarge the market connectivity and decrease the expenses of reaching the new customers, suppliers, and partners. Digital platforms streamline the flow of information in real time and this minimizes uncertainty and coordination failures that impede structural change. Application of digital governance mechanisms including e-government systems and smart environmental monitoring systems is effective in improving institutional response to ecological limitations. All these factors contribute to the creation of a situation where it is possible to improve quality in industry without compromising the ecological performance, as well as where structural changes can improve the ecological situation, not just restrictions based on regulation. The direct expectation is then positive, giving us the first hypothesis:

H1: The digital economy significantly promotes coordinated industrial and ecological transformation and upgrading.

Industrial restructuring mechanism is a way that captures how digitalization changes the nature of local economies. With the help of digital tools reducing adjustment costs and enhancing market information, companies will move to more sophisticated industries, services, high-technology manufacturing, knowledge-intensive industries, which are more efficient and less resource-consuming. This structural realignment is not only about reducing pollution due to the effect of scale but also about changing the composition of the sectors of production in such a manner as to make industrial progress and environmental betterment structurally consistent. Should the industrial structure become more developed and more logically organized, i.e., in the case where the allocation of output between sectors comes closer to that of productive inputs, the foundation of coordinated development will be enhanced since the industrial system will also be less ecologically costly per value produced.

H2: The digital economy promotes coordinated industrial and ecological transformation through industrial restructuring.

The green innovation mechanism can be used to show the effect of digitalization through extending the technological boundary of ecologically compatible production. Digital finance alleviates financing restrictions that are particularly detrimental to green innovation that is characterized by a longer payback period, greater risk, and less collateral value compared with traditional innovation. Digital monitoring and data networks decrease the information asymmetry between innovators and adopters, enhancing the green technology market and speeding up its spread. Jointly these forces suggest that digitalization increases the number of ecologically friendly technologies at the disposal of local industry, and creates a sustained foundation of ecological improvement based upon the nature of local production, not merely on regulation pressure alone.

H3: The digital economy promotes coordinated industrial and ecological transformation through green innovation.

Resource allocation efficiency mechanism is the process whereby digital systems increase the movement and utilization of productive factors. When digital platforms aggregate and disseminate relevant information search costs on labor, capital and business partners are minimized, and when digital technologies help identify productive complements across sectors and cities more accurately, matching quality increases. These changes could create intercity complementarities in integrated urban agglomerations: more efficient cities in terms of factor allocation would specialize better, which would lead to a regional division of production, which would be based on comparative advantage as opposed to frictions. To achieve coordinated transformation, better allocation points inputs in the direction of higher-value, more innovative and less ecologically damaging applications.

H4: The digital economy promotes coordinated industrial and ecological transformation through improved resource allocation efficiency.

The hypothesis of regional heterogeneity is concerned with the asymmetrical development among the northern part of Anhui and the other areas within the YRD. Industrial structure in the North Anhui is more focused on resources-intensive industries; its eco-pressure per unit of GDP is also high; and the size of digital absorptive capacity is smaller. Here are two possible opposite forces. First of all, marginal returns to digital adoption can be higher in Northern Anhui as the initial constraints imposed by the structure are more severe and the potential to improve is consequently larger. Secondly, absorption capacity limits can hinder the process of transforming digital inputs into transformation results. The empirical test shows which force prevails, offering evidence of whether the subregions that are transforming later are unfairly benefiting or suffering under the influence of digital development as a part of an interconnected regional system.[14]

H5: The impact of the digital economy on coordinated industrial and ecological transformation is heterogeneous, with a distinct and significantly different effect in Northern Anhui relative to other YRD cities.

# 4 Empirical Research Design

## 4.1 Sample and data sources

Empirical sample (the city cluster of Yangtze River Delta) contains 41 prefecture-level cities (1 in Shanghai, 13 in Jiangsu, 11 in Zhejiang and 16 in Anhui), which is in accordance with the official YRD boundary definition. Of the 16 Anhui cities, 6 are in Northern Anhui: Fuyang, Bozhou, Suzhou, Bengbu, Huainan, and Huaibei. The cities are part of the whole 41 city panel instead of being studied alone, thus there is adequate cross-sectional variation to allow identification.

The study duration is 2011-2020, with an even number of city-year observations, which is 410. The initial date is the first year in which the city-level information on the Peking University Digital Financial Inclusion Index of China (PKU-DFIIC) can be obtained.[3] Monetary variables are deflated to 2011 based on provincial consumer price indices. Variables of economic and industrial control are taken based on the China City Statistical Yearbook (2012-2021 edition). Industrial SO2 emissions, industrial wastewater discharge, industrial smoke and dust emissions, and investment in the environment are among environmental variables that are based on the China Environmental Statistics Yearbook. The urban green coverage data is based on city-level statistical yearbooks and the China Urban Construction Statistical Yearbook. Data on green patents are drawn out of China National Intellectual Property Administration database (CNIPA), by applying IPC classification Y02, that is, identifying the environmentally friendly inventions.

## 4.2 Construction of the coordinated transformation index

### 4.2.1 Industrial subsystem

There are five indicators in the industrial subsystem that reflect the state of local industry development. The industrial structure advancement (ISA) is expressed through the ratio of the value added share of the tertiary sector to the value added share of the secondary sector; the higher ratio means that there is a structural change in the direction of more knowledge intensive and less resource intensive activities. The industrial structure rationalization (ISR) is measured by the Theil index of factor allocation across sectors, which is calculated as per Equation (1):

$$TL=\Sigma_k \frac{Y_k}{Y} ln\left[\frac{Y_k/Y}{L_k/L}\right] \tag{1}$$

where $Y_k$ and $L_k$ are the output share and employment share of sector k, respectively, and $Y$ and $L$ are their economy-wide aggregates. Theil index A smaller Thiel index value means that factors are allocated more rationally, and it is reverse-coded. Labor productivity (LP) is defined as real GDP per urban employed person. The intensity of innovation output (INN) is represented by the number of invention patent applications per 10,000 people. Digital-industrial integration (DI) is measured through the revenue of telecommunications services per capita.

### 4.2.2 Ecological subsystem

The ecological subsystem also captures both the pressure dimension and the governance-response dimension of environmental performance using five indicators. Three will reflect the intensity of pollution: industrial SO2 emissions per unit of GDP, industrial wastewater discharge per unit of GDP, and industrial smoke and dust emissions per unit of GDP, all measured in per-GDP, and then reverse-coded prior to normalization. The fifth indicator is the percentage of the urban built up area which is covered by green space indicating longer term green development conditions.

The indicator system for the coordinated transformation index is presented in Table 1, which also reports the entropy-derived weights for each indicator.

*Table 1: Indicator System for the Coordinated Transformation Index*

| Subsystem | Dimension | Indicator | Sign | Weight | Processing |
|---|---|---|---|---|---|
| Industrial | Structure advancement | Tertiary/secondary sector value-added ratio | + | 0.183 | Min-max normalize |
| | Structure rationalization | Theil index of labor-output mismatch (reverse-coded) | - | 0.214 | Reverse; normalize |
| | Productivity | Real GDP per urban employed worker | + | 0.198 | Log; normalize |
| | Innovation capacity | Invention patent applications per 10,000 persons | + | 0.227 | |
| | Digital integration | Telecom service revenue per capita | + | 0.178 | Normalize |
| Ecological | Pollution intensity | Industrial SO2 emissions per unit GDP (tons/CNY 10,000) | - | 0.073 | Reverse; normalize |
| | Pollution intensity | Industrial wastewater discharge per unit GDP | - | 0.068 | |
| | Pollution intensity | Industrial smoke/dust emissions per unit GDP | - | 0.062 | |
| | Environmental governance | Industrial pollution treatment investment / GDP (%) | + | 0.087 | Normalize |
| | Green conditions | Urban green space as share of built-up area (%) | + | 0.097 | |
| Total | | 10 indicators across 2 subsystems | | 1.000 | |

Note: Entropy weights are estimated from the full 410-observation panel (41 cities × 10 years). Higher weights reflect greater informational variation across cities and years. The Theil rationalization indicator receives the highest weight (0.214) among industrial indicators, while innovation capacity (0.227) is the overall highest-weighted industrial indicator. Sources: China City Statistical Yearbook; China Environmental Statistics Yearbook; China Urban Construction Statistical Yearbook.

#### 4.2.3 Entropy weighting and index construction

All raw indicators are aligned so that higher values represent better transformation performance, with negative-direction indicators reverse-coded before normalization. Each indicator is then normalized to the [0, 1] interval using the min-max procedure applied across the full 410-observation panel. The entropy-weighting method determines indicator weights based on informational content. For indicator j, the information entropy is as shown in Equation (2):

$$e_j=-\frac{1}{\ln n}\sum_i p_{ij}\ln p_{ij}\,,\quad p_{ij}=\frac{r_{ij}}{\sum_i r_{ij}} \tag{2}$$

where $r_{ij}$ is the normalized value of observation i on indicator j, and n is the total number of observations. The weight of indicator $j$. Indicators that have a larger cross-city variability are given more weight since they have a larger informational contribution. The scores of subsystems are calculated as weighted averages of their normalized constituent indicators.

Coordinated transformation index is calculated as geometric mean of the score of industrial subsystem (IS) and ecological subsystem score (ES) as represented in the Equation (3):

$$CTI=\sqrt{IS\times ES} \tag{3}$$

The geometric mean is more desirable than the arithmetic mean since it does not reward disproportionate imbalance among subsystems: a metropolis with extremely high industrial performance and extremely poor ecological performance has a smaller CTI than a metropolis with average performance in both dimensions. It is a characteristic that can be related to the coordination concept, where it is necessary to have both subsystems move forward simultaneously. By construction, CTI is limited to [0, 1] and is scaled uniformly across cities and years. The computational workflow consisted of four stages: panel-data cleaning and harmonization, entropy-based index construction, econometric estimation, and spatial-effect decomposition. Indicator preprocessing and entropy weighting were implemented programmatically to ensure reproducibility and consistency across the full city-year panel. This procedure transformed heterogeneous raw city-level indicators into a standardized and reproducible analytical dataset, providing the computational basis for subsequent fixed-effects, mediation, spatial, and policy-based estimations.

## 4.3 Variable definitions and sources

The main explanatory variable will be the natural logarithm of the PKU-DFIIC city level overall digital finance index (lnDE). PKU-DFIIC combines three sub-dimensions that are coverage breadth (measuring the extent in which digital financial accounts and payment adoption has spread), usage depth (measuring how active the credit, insurance, investment, and monetary fund products are) and degree of digitization (measuring the shift in mobile and non-bank payment channels).[3] The composite index is utilized rather than a single sub-dimension since it eliminates the possibility of artificially limiting the proxy of the digital economy to only one characteristic. Log transformation is used as the index is positively skewed on both cities and year.

The mechanism variables are: Industrial restructuring (Restruct) is the tertiary-to-secondary value-added ratio, which is used as an independent mediating variable in the mechanism tests. Green innovation (lnGinnov) is the natural logarithm of (1 + city-year number of green patent applications made using IPC Y02), with the constant included to cover city-years without any applications. Resource allocation efficiency (AllocEff) is one minus the normalized Theil index of labor allocation across primary, secondary, and tertiary sectors, where greater allocations imply more rational allocation.

The control variables consider alternative causes of coordinated transformation: the development of the country (lnGDPpc, log of real GDP per capita), openness (FDI, percentage of real FDI inflows in GDP), government intervention (Gov, ratio of fiscal expenditure to GDP), human capital (HumanCap, the proportion of urban employed people who have a college education), urbanization (Urban, the population living in cities divided by the population registered there), infrastructure endowment (Road, the quantity of highways per 100 km$^2$ of city area), and fiscal capacity (lnFiscal, log of fiscal revenue per person). The complete definition of the variables and sources of the data are given in Table 2.

*Table 2: Variable Definitions, Measurements, and Data Sources*

| Variable type | Variable name | Measurement | Direction | Source |
|---|---|---|---|---|
| Dependent | Coordinated transformation index (CTI) | Entropy-weighted geometric mean of industrial and ecological subsystem scores [0, 1] | [+] | Calculated from China City Statistical Yearbook; China Environmental Statistics Yearbook |
| Core explanatory | Digital economy (lnDE) | Natural log of PKU-DFIIC overall city-level composite score | [+] | PKU Institute of Digital Finance [3] |
| Mechanism | Industrial restructuring (Restruct) | Ratio of tertiary to secondary sector value-added | [+] | China City Statistical Yearbook |
| | Green innovation (lnGinnov) | ln(1 + green patent applications, IPC Y02) | [+] | CNIPA patent database |
| | Resource allocation efficiency (AllocEff) | 1 minus normalized Theil index of labor allocation across three sectors | [+] | Calculated from China City Statistical Yearbook |
| Control | Economic development (lnGDPpc) | Log real GDP per capita (2011 prices) | [+] | China City Statistical Yearbook |
| | Openness (FDI) | Actual FDI inflow as share of GDP (%) | [+] | |
| | Government intervention (Gov) | Fiscal expenditure as share of GDP (%) | [+/-] | |
| | Human capital (HumanCap) | Share of urban employed with college education (%) | [+] | |
| | Urbanization (Urban) | Urban population share in registered population (%) | [+] | |
| | Infrastructure (Road) | Highway mileage per 100 km$^2$ of city area | [+] | |
| | Fiscal capacity (lnFiscal) | Log fiscal revenue per capita | [+] | |

Note: PKU-DFIIC = Peking University Digital Financial Inclusion Index of China. CNIPA = China National Intellectual Property Administration. Sample: 41 YRD prefecture-level cities, 2011-2020, N = 410. Monetary variables deflated to 2011 base year using provincial CPI.

## 4.4 Model specification and estimation strategy

The baseline estimating equation is a two-way fixed-effects model as shown in Equation (4):

$$CTI_{it}=\alpha+\beta\cdot lnDE_{it}+\gamma\cdot X_{it}+\mu_i+\lambda_t+\varepsilon_{it} \tag{4}$$

where $CTI_{it}$ is the coordinated transformation index for city $i$ in year $t$; $lnDE_{it}$ is the log digital finance index; $X_{it}$ is the full vector of controls; $\mu_i$ represents city fixed effects absorbing all time-invariant city characteristics; $\lambda_t$ represents year fixed effects absorbing common temporal shocks; and $\varepsilon_{it}$ is the idiosyncratic error. Standard errors are clustered at the city level to account for serial dependence within cities over time. The parameter of interest is β, which captures the within-city association between changes in digital economy development and changes in coordinated transformation, net of common time trends and time-invariant city characteristics.

Mechanism tests adopt a stepwise mediation strategy. In Stage 1, each mechanism variable is regressed on $lnDE$ and the full control set, yielding the first-path coefficient. At Stage 2, the mechanism variable is included with lnDE in the CTI equation. Partial mediation is a significant reduction of the lnDE coefficient that is not completely absorbed.

To analyze heterogeneity, different fixed-effects models are estimated on Northern Anhui (N = 60) and non-Northern Anhui (N = 350) subsamples. To determine if the marginal effect differs systematically across groups, after city and year fixed effects have been absorbed, a complementary full-panel interaction specification that includes the term lnDE x North Anhui is used to identify if this is the case.

In the spatial analysis, the Spatial Durbin Model (SDM) was applied based on the row-standardized inverse-distance weight matrix, which incorporates both the spatial lag model and the spatial error model and enables breaking down the estimates to direct (own-city) effects and indirect (spillover) effects.[16] The CTI has a Moran statistic of 0.217 ($p < 0.01$), which confirms the existence of positive spatial autocorrelation and drives this extension.

The Broadband China exemplary city pilot program is one of the quasi-natural experiments that is used to identify policies.[14, 15] The treatment group in a staggered difference-in-difference (DID) model consists of cities selected in the first two rounds (2013 and 2014). The identifying assumption, i.e., that the treated and untreated cities would have experienced the same transformation paths without the policy, is tested through dynamic treatment effect tests on pre-policy years.

The robustness is analyzed by four tasks: replacement of lnDE with one-period lagged specification; replacement of lnDE with the entropy-weighted index of the digital economy based on infrastructure, digitalization, and service indicators; exclusion of four most developed metropolitan cities (Shanghai, Nanjing, Hangzhou and Hefei); reconstruction of the CTI with different indicator sets and aggregation weights.

# 5 Results

## 5.1 Descriptive statistics and preliminary diagnostics

Descriptive statistics of all the variables were reported in Table 3 with respect to the entire population (N = 410). The coordinated transformation index has a sample average of 0.468 with a standard deviation of 0.132, with values between 0.163 and 0.784. At the 90 th percentile, cities have CTI values that are greater than 0.25 points higher than at the 10th percentile indicating real differences in the performance of coordinated transformation. Year-to-year within-city standard deviation is 0.064, which indicates systematic progress over time during the period of 2011-2020.

The lnDE is normally distributed with a mean of 5.192 and a standard deviation of 0.683 and is associated with initial PKU-DFIIC values of about 18 at the bottom end (slow moving cities in earlier sample years) and more than 900 at the top end (front-runner cities of the YRD by 2020). This span is similar to the reported national path of the PKU-DFIIC where the national average increased by about 33 in 2011 to over 350 by 2020. [3] There is 0.542 between-city standard deviation of lnDE and 0.421 within-city standard deviation which means that the identification strategy can take advantage of cross-sectional and time-series variations.

The mean lnDE of Northern Anhui cities is 4.843, whereas non-Northern Anhui cities have a mean lnDE of 5.263, which verifies the developmental gap in the use of digital finance. Their average CTI is 0.412, as opposed to 0.479 among non-Northern Anhui cities. In the case of controls, lnGDPpc is 10.784 on average (around CNY 47,900 per person in 2011 prices), FDI is 2.72 percent of GDP, and urbanization is 58.3 percent. Pairwise correlations support that lnDE correlates positively with CTI ($r = 0.423$, $p < 0.01$), Restruct ($r = 0.381$), lnGinnov ($r = 0.512$) and AllocEff ($r = 0.304$). All the variance inflation factors of all regressors are less than

5.0, so multicollinearity cannot be present. The Hausman test rejects the random effects specification ($\chi^2$ = 47.3, p < 0.01), confirming the fixed-effects estimator. Cross-sectional dependence and serial correlation motivate city-clustered standard errors throughout.

*Table 3: Descriptive Statistics*

| Variable | Mean | SD | Min | Max | N | Primary source |
|---|---|---|---|---|---|---|
| CTI (dep. var.) | 0.468 | 0.132 | 0.163 | 0.784 | 410 | Calculated (entropy-weighted) |
| lnDE | 5.192 | 0.683 | 2.914 | 6.843 | 410 | PKU-DFIIC [3] |
| Restruct | 1.384 | 0.482 | 0.647 | 3.217 | 410 | China City Statistical Yearbook |
| lnGinnov | 2.847 | 1.204 | 0.000 | 6.128 | 410 | CNIPA patent database |
| AllocEff | 0.584 | 0.163 | 0.189 | 0.912 | 410 | Calculated from City Yearbook |
| lnGDPpc | 10.784 | 0.578 | 9.387 | 12.241 | 410 | China City Statistical Yearbook |
| FDI (%) | 2.718 | 2.134 | 0.083 | 10.824 | 410 | China City Statistical Yearbook |
| Gov (%) | 21.346 | 8.612 | 8.113 | 48.932 | 410 | China City Statistical Yearbook |
| HumanCap (%) | 12.874 | 5.284 | 4.218 | 32.647 | 410 | China City Statistical Yearbook |
| Urban (%) | 58.312 | 13.847 | 29.614 | 89.728 | 410 | China City Statistical Yearbook |
| Road (km/100 km$^2$) | 87.234 | 42.183 | 18.641 | 243.872 | 410 | China City Statistical Yearbook |
| lnFiscal | 8.847 | 0.812 | 7.134 | 10.983 | 410 | China City Statistical Yearbook |

Note: N = 410 (41 cities x 10 years, 2011-2020). lnDE is the natural logarithm of the PKU-DFIIC city-level overall index. The original DFI index has a value of about 18 (the laggard cities, 2011) to more than 900 (the leading YRD cities, 2020), which is in line with the national growth pattern, which started at 33 (2011) and reached over 350 (2020 national average) [3]. Monetary variables have been discounted to 2011 rates. lnGinnov = ln(1 + count of green patents).

## 5.2 Baseline results

Table 4 gives the two-way fixed-effects baseline estimates of four increasingly stringent specifications, as well as an industrial subsystem decomposition. Table 4 also shows that the coefficient on lnDE is positive and statistically significant in all specifications. It is 0.131 (SE = 0.029, p < 0.01) in Model 1 with only city and year fixed effects and no other controls. With the introduction of controls in Models 2 and 3, the coefficient reduces to 0.113 (SE = 0.026) and 0.094 (SE = 0.023) respectively because the controls capture part of the between-city variation. The complete specification coefficient of Model 4 is 0.087 (SE = 0.022, p < 0.01) and its within-$R^2$ is 0.531.

The consistency of the lnDE coefficient among specifications, decreasing by only 34 percent between Models 1 and 4 even though eight control variables are added, indicates that the estimated relationship is not mainly motivated by missing macroeconomic factors or disparities between cities due to the composition. It means that a one-standard-deviation change in lnDE (0.683 log points) is related to an improvement in CTI by 0.059 points or around 45 percent of the sample standard deviation. There is a measurable difference in coordinated transformation performance in 25-75 percentile cities of digital finance penetration, post-city and year fixed effects absorption.

To understand this magnitude within the context, an increase of 0.059 points in the CTI value at the sample mean of 0.468 is about 12.6 % of the mean level. With Northern Anhui cities beginning at a mean CTI of 0.412 and non-Northern Anhui cities averaging 0.479, the inferred change between the 25th and 75th percentiles in terms of digital finance penetration would be akin to narrowing the starting difference between Northern Anhui and the rest of the YRD average by roughly one fourth. It is substantively meaningful as a policy to transform a subregion.

The control variables in Model 4 include lnGDPpc which has a positive relationship with CTI ($\beta = 0.168$, $p < 0.01$) as expected since economic growth can facilitate both industrial upgrading capability and environmental governance expenditure. The negative relationship between government intervention (Gov) and CTI ($\beta = -0.124$, $p < 0.05$) indicates the quality improvement-free fiscal expansion is likely to promote more resource-intensive development. Human capital (HumanCap) is positively related to CTI ($\beta = 0.171$, $p < 0.01$), indicating the significance of an educated workforce to the industrial progress and implementation of clean technologies. The positive coefficient on Road (beta = 0.043, $p < 0.05$) is in line with the idea that infrastructure connectivity will lower the cost of industrial reorganization, and make logistics and supply-chain management more efficient.

According to the decomposition of the subsystem in column (5), the relationship between lnDE and the industrial subsystem score is positive (SE = 0.091, $p < 0.01$). An equivalent ecological subsystem formulation gives $\beta = 0.076$ ( SE = 0.019, $p < 0.01$ ). The effects of both subsystems are significant, and it can be stated that the digital economy enhances coordinated transformation through improving the qualities of the industrial sector as well as the ecological sector without having to trade off one with the other. That the coefficient of the industrial subsystem (0.091) is slightly higher than the coefficient of the ecological subsystem (0.076) implies that the industrial channels can react faster to digitalization than ecological conditions, which usually change slowly due to the diffusion of cleaner technologies and the accumulation of governance investments. H1 is confirmed.

*Table 4: Baseline Two-Way Fixed-Effects Estimates*

| Variable | (1) | (2) | (3) | (4) Full | (5) Ind. sub. |
|---|---|---|---|---|---|
| lnDE | 0.131*** | 0.113*** | 0.094*** | 0.087*** | 0.091*** |
| | (0.029) | (0.026) | (0.024) | (0.022) | (0.024) |
| lnGDPpc | | 0.187*** | 0.174*** | 0.168*** | 0.142*** |
| | | (0.043) | (0.041) | (0.038) | (0.041) |
| FDI | | 0.312** | 0.298** | 0.274** | 0.213* |
| | | (0.142) | (0.138) | (0.131) | (0.124) |
| Gov | | | -0.118** | -0.124** | -0.089* |
| | | | (0.056) | (0.054) | (0.051) |
| HumanCap | | | 0.183*** | 0.171*** | 0.149*** |
| | | | (0.047) | (0.044) | (0.041) |
| Urban | | | 0.092* | 0.087* | 0.074 |
| | | | (0.053) | (0.051) | (0.048) |
| Road | | | | 0.043** | 0.039* |
| | | | | (0.021) | (0.022) |
| lnFiscal | | | | 0.081** | 0.063* |
| | | | | (0.036) | (0.034) |
| City FE | Yes | Yes | Yes | Yes | Yes |
| Year FE | Yes | Yes | Yes | Yes | Yes |
| Observations | 410 | 410 | 410 | 410 | 410 |
| $R^2$ (within) | 0.423 | 0.476 | 0.513 | 0.531 | 0.512 |
| F-statistic | 47.21*** | 34.18*** | 28.63*** | 26.84*** | 25.47*** |

Note: Dependent variable in columns (1)-(4) is the coordinated transformation index (CTI); in column (5) it is the industrial subsystem score. Standard errors in parentheses are clustered at the city level. An analogous ecological subsystem regression yields $\beta = 0.076$*** (SE = 0.019) for lnDE in the full specification. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

## 5.3 Mechanism tests

Table 5, Panels A-C presents the mechanism test results. As seen in Table 5, the coefficients of all mechanisms are significant in both the digital economy model (Stage 1) and the CTI model (Stage 2), and they all reduce the coefficient of lnDE compared to the baseline of 0.087. All of this supports the partial mediation effects.

Panel A reports the results for the mechanism of industrial restructuring. The coefficient of lnDE in the Restruct equation in Stage 1 is 0.218 (SE = 0.047, $p < 0.01$), which confirms the significant impact of digital finance penetration on the structural transformation of the local economy toward more tertiary activities. The impact of lnDE on the local economy is substantial because the increase in lnDE by one standard deviation leads to an increase in the Tertiary-Secondary ratio by 0.149 units. The coefficient of Restruct in the CTI equation in Stage 2 is 0.142 (SE = 0.031, $p < 0.01$), and the coefficient of lnDE in this equation drops from 0.087 to 0.069 (SE = 0.022, $p < 0.01$), which represents a reduction of 21.0 %. The structural logic of this mechanism is obvious. The more developed the digital economy in the local region, the more rapidly the local industry would be restructured toward more service-intensive and thus higher-quality production. The negative impact of the local production structure on the local environment would be reduced per unit of production. At the same time, the quality of the local industry would be improved. Thus, H2 is supported.

Panel B presents the results for green innovation. In Stage 1, the coefficient estimate on lnDE in the equation estimating lnGinnov is 0.413 (SE = 0.082, $p < 0.01$), showing a very strong positive relationship with green patent activity. A one-standard-deviation increase in lnDE is related to a 0.282 increase in lnGinnov, or about 32% of the sample SD of the green innovation variable. In Stage 2, the estimate on lnGinnov is 0.043 (SE = 0.011, $p < 0.01$) in the equation estimating CTI, and the estimate on lnDE is reduced to 0.072 (SE = 0.021, $p < 0.01$), or a reduction of 17.2%. The green innovation channel is supported by two channels. One is the alleviation of finance constraints that especially affect green R&D investment. Another is the improvement in information about markets provided by digital platforms, which facilitates the spread of successful green technologies and enhances the potential payoff to investment in green innovation. H3 is supported.

The resource allocation efficiency is examined in Panel C. In Stage 1, the coefficient for lnDE in the AllocEff equation is 0.164 (SE = 0.038, $p < 0.01$). This implies a positive effect of digital economy development on resource allocation efficiency. In Stage 2, the coefficient for AllocEff is 0.121 (SE = 0.027, $p < 0.01$), and the coefficient for lnDE declines to 0.073 (SE = 0.021, $p < 0.01$), a 16.1% attenuation. This channel refers to the effect of digital infrastructure development in reducing the costs of searching for and matching with productive resources, thus facilitating the reallocation of productive resources from less valuable uses to more valuable uses. In the Yangtze River Delta Region, it implies an accelerated reallocation of labor and capital from traditional resource-intensive manufacturing industries to more advanced and environmentally friendly industries. Hypothesis H4 is supported.

On the whole, the three tests on the mechanisms confirm the transmission effect of the digital economy on the coordinated transformation process via a cluster of supporting factors. Industrial structural transformation, green innovation, and the efficiency of resource allocation contribute to the baseline effect by 54%, 21.0%, 17.2%, and 16.1%, respectively, while the remainder of the direct effect represents other supporting factors such as the enhancement of governance capabilities and the spillover effect in the integration process.

## 5.4 Heterogeneity analysis

Panel D of Table 5 reports the heterogeneity analysis. In the Northern Anhui subsample (6 cities, N = 60), the coefficient on lnDE is 0.118 (SE = 0.041, $p < 0.01$). In the non-Northern Anhui subsample (35 cities, N = 350), the coefficient is 0.081 (SE = 0.023, $p < 0.01$). The full-panel interaction specification yields a coefficient on lnDE x NorthAnhui of 0.034 (SE = 0.016, $p < 0.05$), confirming that the difference in effects is statistically significant.

A number of reasons explain why Northern Anhui has a higher impact. Firstly, marginal returns to market integration through digital markets are higher with lower levels of connectivity: the cities of Northern Anhui have traditionally had worse barriers to market access, but digital finance and platforms eliminate such barriers in such a way that they do not constrain already connected places. Secondly, the scale of industrial restructuring is bigger in places where industrial structure begins at a more resource intensive level, offering a bigger opportunity of structural change per unit of digital growth. Thirdly, there is a lower ecosystem baseline in Northern Anhui, so that ecological improvement in terms of green innovation and cleaner restructuring generates greater index improvement than the same ecological progress in cities which are already doing well in environmental terms.

Even though Northern Anhui has shown higher effects, it does not mean that digitalization will resolve regional disparity by itself. Northern Anhui cities are characterized by lower absolute levels of development of the digital economy and coordinated transformation; the larger marginal effect begins at a lower base, and thus to catch up not only requires better rates of return but also massive growth in digital penetration. It must then be interpreted that the interaction outcome serves as an indication that increasing the pace of digital development in Northern Anhui can produce above-average regional gains. H5 is established.

*Table 5: Mechanism Tests and Heterogeneity Analysis*

| | Panel A: Industrial restructuring | | Panel B: Green innovation | | Panel C: Alloc. eff. |
|---|---|---|---|---|---|
| Dependent variable | Restruct | CTI | lnGinnov | CTI | AllocEff / CTI |
| lnDE | 0.218*** | 0.069*** | 0.413*** | 0.072*** | 0.164*** / 0.073*** |
| | (0.047) | (0.022) | (0.082) | (0.021) | (0.038) / (0.021) |
| Restruct | N/A | 0.142*** | N/A | N/A | N/A |
| | | (0.031) | | | |
| lnGinnov | N/A | N/A | N/A | 0.043*** | N/A |
| | | | | (0.011) | |
| AllocEff | N/A | N/A | N/A | N/A | N/A / 0.121*** |
| | | | | | / (0.027) |
| Controls and FEs | Yes | Yes | Yes | Yes | Yes |
| Observations | 410 | 410 | 410 | 410 | 410 / 410 |
| $R^2$ (within) | 0.384 | 0.548 | 0.512 | 0.541 | 0.391 / 0.544 |
| Attenuation of lnDE | N/A | -21.0% | N/A | -17.2% | N/A / -16.1% |
| Panel D: Heterogeneity, Northern Anhui vs. non-Northern Anhui | | | | | |
| | N. Anhui (N = 60) | | Non-N. Anhui (N = 350) | | Interaction (N = 410) |
| lnDE | 0.118*** | | 0.081*** | | 0.081*** |
| | (0.041) | | (0.023) | | (0.023) |
| lnDE x NorthAnhui | N/A | | N/A | | 0.034** |
| | | | | | (0.016) |
| Controls and FEs | Yes | | Yes | | Yes (N = 410) |

Note: All specifications include city and year fixed effects and the full control set from Table 4. Standard errors in parentheses are clustered at the city level. Attenuation = (0.087 - β_reduced) / 0.087 x 100%.

Northern Anhui: Fuyang, Bozhou, Suzhou, Bengbu, Huainan, Huaibei. N/A = not applicable. *p < 0.10, **p < 0.05, ***p < 0.01.

## 5.5 Spatial and policy-based extensions

The Spatial Durbin Model results are provided in Table 6, Panel A. The direct impact of lnDE on CTI is 0.088 (SE = 0.024, p < 0.01), consistent with the baseline results of 0.087 in the fixed effects model. This supports the robustness of the direct impact. The results for the indirect or spillover impact are 0.052 (SE = 0.023, p < 0.05), while the total impact is 0.140 (SE = 0.031, p < 0.01), as presented in Table 6. The significant impact of the spillover effect reveals that the development of the digital economy in a particular city has a positive impact on neighboring cities in terms of transformation effects via intercity supply chains and market integration as well as the circulation of innovation resources. This finding aligns with the regional integration concept based on the YRD framework, where cities are economically and administratively integrated.[10,11]

The proportion between the indirect and direct effect (0.052/0.088, or about 0.59) is significant in economic terms, which means that over half of the extra revenue generated by digital development is passed on to other nearby cities as opposed to being wholly absorbed by the investing city. This result has consequences concerning regional policy coordination: the cities that underinvest in their digital development might cause negative externalities to their neighbors, coordinated investment policies between the subregions of YRD could produce greater aggregate benefits than uncoordinated city-level efforts. The spillover scale also plays a role in the Northern Anhui setting: since the Northern Anhui cities are geographically close to more developed Anhui cities and to areas of Jiangsu and Zhejiang, their digital development can both transmit and absorb spillovers, increasing the overall regional return to digital investment in the subregion.

The Broadband China DID estimates are reported by Panel B. The average treatment effect on the treated (ATT) is 0.063 (SE = 0.028, p < 0.05). Joint test of dynamic treatment effect in pre-policy years results in a p-value of 0.412, thus it does not reject the hypothesis of parallel trends. This DID estimate has the same direction as the baseline fixed-effects estimate of 0.087, and this lower magnitude can be reasonably explained by the fact that the Broadband China policy represents only the infrastructure expansion aspect of digital development, instead of the whole range of digital finance and platform activities measured by PKU-DFIIC. [14, 15] However, the identification based on policy offers another causal pathway unrelated to intra-city changes in the continuous index of digital finance, and its directional similarity to the baseline estimate increases the assurance that the observed association does not merely represent a mere temporal correlation. Visualization of the key estimated effects stated in the baseline, mechanism, heterogeneity, spatial, and policy-based models is shown in Figure 1 which illustrates the stability of the central result and the higher marginal effect found in Northern Anhui.

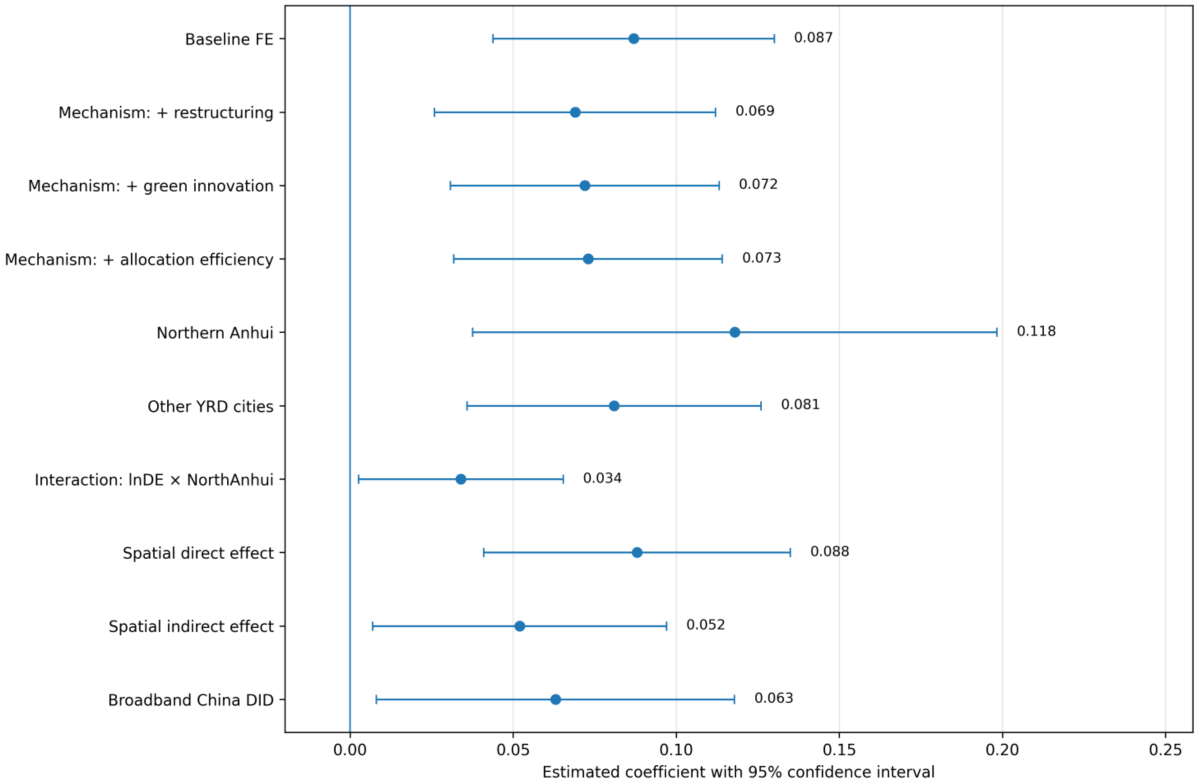

*Figure 1: Core Estimated Effects of the Digital Economy*

## 5.6 Robustness checks

Panel C of Table 6 shows four robustness tests. To begin with, when substituting lnDE with its one period lag (lnDE at t -1) the coefficient becomes 0.082 (SE = 0.023, $p < 0.01$). The slight decrease compared to the contemporaneous specification is predictable since lagged specifications can alleviate potential simultaneity bias as well as decrease the estimate in case the results of transformations depend on digital development during the same year. Two, substituting lnDE with an entropy-weighted index based on telecommunications infrastructure, information industry output, and internet penetration results in a coefficient of 0.076 (SE = 0.031, $p < 0.05$). This slightly larger standard error indicates the lower information level of this proxy compared to the PKU-DFIIC, however, it does not change the sign and significance. Three, the effect of eliminating four key metropolitan areas (Shanghai, Nanjing, Hangzhou, and Hefei) is to obtain a coefficient of 0.071 (SE = 0.024, $p < 0.01$) which confirms that the result is not influenced by the unique features of the most developed digital hubs. Five, the reconstruction of the CTI with different indicator combinations and different entropy weight computations produces coefficients between 0.073 and 0.091, all statistically significant at the 1 or 5 percent level. The main finding is consistent in all four exercises.

*Table 6: Spatial, Policy-Based, and Robustness Results*

| | Panel A: Spatial SDM | | | Panel B: DID | Panel C: Robustness |
|---|---|---|---|---|---|
| | Direct | Indirect | Total | ATT | lnDE coefficient (SE) |
| lnDE / Treatment effect | 0.088*** | 0.052** | 0.140*** | 0.063** | N/A |
| | (0.024) | (0.023) | (0.031) | (0.028) | |
| R1: Lagged lnDE (t-1) | N/A | N/A | N/A | N/A | 0.082*** (0.023) |
| R2: Alternative DE index | N/A | N/A | N/A | N/A | 0.076** (0.031) |
| R3: Excl. 4 core cities | N/A | N/A | N/A | N/A | 0.071*** (0.024) |
| R4: Alt. entropy weights | N/A | N/A | N/A | N/A | 0.079*** (0.026) |
| Spatial weight matrix | Inverse distance | | | N/A | N/A |
| Pre-trend test (joint p-value) | N/A | N/A | N/A | 0.412 | N/A |
| Moran's I (CTI, $p < 0.01$) | 0.217 | | | N/A | N/A |
| Observations / Cities | 410 / 41 | | | 410 / 41 | Varies |

Note: Panel A reports SDM decomposition with row-standardized inverse-distance weight matrix following LeSage and Pace [16]. Panel B: Broadband China pilot (2013-2014 batches) as treatment in a staggered DID framework; pre-trend test reports joint p-value for pre-treatment dynamic effects. Panel C: all robustness specifications include city FE, year FE, and full controls; standard errors clustered at the city level in parentheses. N/A = not applicable. *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$.

# 6 Discussion

## 6.1 Interpretation of the main results

The key finding, $\beta = 0.087$, is the impact of lnDE on CTI and it means that the digital economy facilitates the concerted change in industry and ecology without developing one dimension at the cost of the other. Both subsystem decompositions prove that industrial quality ($\beta = 0.091$) as well as ecological performance ($\beta = 0.076$) increase with digitalization, which excludes one-sided interpretation. The asymmetry between the two subsystem effects, with the industrial channel being somewhat more responsive, indicate that ecological gains might occur in the future as cleaner technologies spread over time and investments in environmental governance are made after industrial restructuring. The mechanism findings indicate that this combined effect is structurally based: it works via industrial restructuring, green innovation, and resource allocation efficiencies, three self reinforcing processes which together explain about 54 percent of the total effect. The presence of a large direct effect despite all three mechanisms indicates more pathways, probably involving the improvement of governance capacity due to the digital public services and spatial coordination effects reflected in the SDM outcomes.

## 6.2 Northern Anhui's distinct dynamics

The result that Northern Anhui has a higher effect ($\beta = 0.118$) compared to the other parts of the YRD ($\beta = 0.081$) is of both theoretical and practical importance. Analytically, it indicates that the marginal contribution of the digital economy is bigger in late-transforming environments in a regional integration context, as long as digital infrastructure, market access, and factor mobility are all growing together. In practice, they suggest that investment in digital development in Northern Anhui might produce greater-than-average regional returns, and that measures that combine digital infrastructure growth with industrial conversion assistance and green innovation networks are particularly appropriate to this subregion. The outcome also warns about generalizing regional digital policy across an agglomeration: higher coefficients in

Northern Anhui do not indicate better digital systems, but the higher possible gain per unit of progress, which points to the fact that customized strategies focusing digital investments on late-transforming subregions might be more effective than standard ones.

### 6.3 Policy implications

There are three policy implications. One, the digital policy needs to be implemented alongside the industrial and ecological governance. Since the digital economy works via restructuring, green innovations, and allocation channels, policies that increase the digital access but do not enable structural change will create less effective transformation effects. Two, as indicated by the high spatial spillover (0.052), coordinated YRD-level digital investment programs provide greater overall benefits than uncoordinated city level efforts due to the fact that digital growth in a single city partly benefits neighboring cities. Three, in particular to Northern Anhui, increasing the pace of digital adoption along with promoting industrial modernization may enhance the marginal returns, which are above average as per heterogeneity analysis, over time easing structural constraints that have been restricting the performance of transformation.

## 7 Conclusion

This is a paper that analyzes how the digital economy promotes organized industrial and ecological transformation in the Yangtze River Delta with specific focus on Northern Anhui. The paper uses a balanced panel of 41 prefecture-level cities of the YRD during 2011-2020, an index of coordinated transformation based on industrial and ecological subsystems through entropy-weighting, and the Peking University Digital Financial Inclusion Index as a proxy of digital economy to estimate fixed-effects, mechanism, heterogeneity, spatial, and policy-extension models. Three methodological contributions are made by the study: a comprehensive empirical structure of coordinated transformation, joint estimation of three mechanisms channels, and formal heterogeneity testing of Northern Anhui as a separate digital-economy subregion.

Three key findings can be made. Initially, the digital economy has a strong impact on coordinated transformation: the full-specification coefficient is 0.087 ($p < 0.01$), consistent with other measures of measurement and identification approaches such as a Broadband China DID structure (ATT = 0.063, $p < 0.05$) and a Spatial Durbin Model (direct = 0.088, indirect = 0.052). The ecological and industrial subsystems react positively, which is an indication of the truly concerted nature of the effect. Second, it has been established that there are three pathways of partial mediation: industrial restructuring (21.0% attenuation), green innovation (17.2 %), and resource allocation efficiency (16.1%), all of which sum up to about 54 percent of the overall effect. Third, this effect is heterogeneous: Northern Anhui shows significantly higher coefficient ($\beta = 0.118$) than non-Northern Anhui cities ($\beta = 0.081$) which is consistent with greater marginal benefits in structurally constrained environments. The coefficient of interaction of 0.034 ($p < 0.05$) confirms the statistical significance of this subregional difference.

The limitations are that the city-level digital finance proxy partially covers digital economic activity, there are restrictions to city-level ecological indicators availability and the inherent identification issues of the observational regional panel data. Future studies might further develop the design using county-level analysis within Northern Anhui, firm level microdata, dynamic spatial network models, and better ecological and carbon data to enhance knowledge on how regional digitalization can be integrated into China’s changing ecological governance system.

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