Marketized Allocation Efficiency of Data Factors and Green Total Factor Productivity: Dynamic and Spatial Effects in Hunan Province

Yuxuan Deng*

School of Economics and Trade, Hunan University, Changsha, 410006, China
*Correspondence: yuxuandeng@hnu.edu.cn

Abstract. Understanding how the market-oriented allocation efficiency of data factors influences green total factor productivity (GTFP) is essential for regional sustainable development. Using panel data of 14 prefecture-level cities in Hunan Province (2010–2023), this study measures data factor allocation efficiency with Pythagorean fuzzy TOPSIS and GTFP with the Global Malmquist–Luenberger index, then identifies dynamic and spatial effects via system GMM and a spatial Durbin model. Allocation efficiency exhibits a single-pole-dominated, east-high-west-low pattern. One-period-lagged allocation efficiency significantly drives GTFP at the 1% level, with a transmission cycle of approximately one year, robust across specifications. Effect decomposition suggests that local efficiency gains may generate competitive pressure on neighbors, potentially a siphon-type spatial dynamic. Environmental regulation shows short-term inhibition consistent with the compliance-cost hypothesis. The findings provide empirical evidence for deepening data factor market reform and coordinating regional green development.

Keywords: data factor marketization; green total factor productivity; sustainable development; spatial spillover; system GMM.

1 Introduction

Green total factor productivity (GTFP) internalizes energy consumption and pollution emissions into efficiency evaluation, directly measuring the integration of economic output and environmental cost, and has become central to assessing green development and regional sustainability. As China shifts toward high-quality development, identifying GTFP drivers—especially emerging factors such as data—is critical. Data has been formally recognized as a novel production factor, and China's Opinions on Building Data Basic Institutions places data factor marketization reform at the forefront. Because data factors possess non-rivalry, high permeability, and low replication cost, their efficient allocation may simultaneously enhance productivity and reduce resource waste. Whether this translates into measurable green gains at the sub-provincial level remains open, particularly for central provinces whose industrial structures differ from the consumer-internet-dominated coast. Hunan, with capital-

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and technology-intensive manufacturing and its designation as a national data factor pilot zone, provides a distinctive setting. Three gaps remain: prefecture-level evidence within provinces is scarce; the dynamic lagged impact of data factor allocation efficiency on GTFP and its joint temporal–spatial modeling are underexplored; and the decomposition of local versus neighborhood effects has received limited attention. This paper measures data factor allocation efficiency using Pythagorean fuzzy TOPSIS with entropy weighting, and GTFP using the Global Malmquist–Luenberger index, for 14 prefecture-level cities in Hunan over 2010–2023. System GMM identifies the dynamic lagged driving effect, and a spatial Durbin model decomposes direct, indirect, and total effects. Contributions: (1) a measurement system balancing inter-provincial comparability with inter-city differentiation; (2) a framework jointly identifying temporal and spatial mechanisms; and (3) evidence on competitive spatial dynamics for regional policy.

2 Literature Review and Theoretical Foundation

Data has evolved into an independent key production factor. Shi and Sun confirm that data factors significantly enhance enterprise TFP, with stronger effects under deeper industrial integration [1]; their low cost, non-rivalry, and low replication cost distinguish them from traditional factors [2]. A market-oriented allocation system centered on rights confirmation, pricing, and trading is required; Yang et al. show that government-participated data trading platforms promote regional development [3]. Liu and Liu provide a systematic institutional framework for data as a production factor [4]. High-quality development centers on transforming development patterns through new quality productive forces and TFP; Ren and Wen propose effectiveness and coordination criteria [6]. Measurement follows two routes: TFP and its green extensions [7][8], and multi-dimensional indicator systems [9][10][15] revealing an east-high-west-low pattern. Ge and Wu confirm the digital economy promotes high-quality development through efficiency and structural optimization [11]; Sheng and Liu's digital economy development index similarly reveals marked spatial differentiation [5]. GTFP internalizes energy and pollution into the efficiency frontier, making it the appropriate benchmark for the synergy of data factor allocation and green transformation, while FDI has been shown to affect enterprises' GTFP [14]. Data factors enhance TFP through digital transformation with a threshold for value release [1], while trading platforms reduce decision costs and optimize allocation [3]. Fan and Wu find human capital moderates digitalization's growth effect [12]; She et al. find low-carbon pilots improve GTFP via innovation and upgrading [13]. The causal chain is: data factor marketization → resource optimization and technological progress → GTFP change. Spatially, Yao and Hu find the digital economy exerts a negative spillover on neighbors' innovation, indicating a siphon effect [19], providing clues for this paper's spatial examination.

3 Materials and Methods

3.1 Variable Selection and Model Specification

The dependent variable is GTFP, which incorporates undesirable outputs such as energy consumption and SO2 emissions. This paper uses the Global Malmquist–Luenberger (GML) index, which constructs a global production possibility set from all DMUs over the period and measures distance to the frontier via a directional distance function, overcoming cross-period non-comparability. Core expressions are Equations (1)–(5):

$$M_t^G = \frac{1+\vec{D}_G(x^t,y^t,b^t;g)}{1+\vec{D}_G(x^{t+1},y^{t+1},b^{t+1};g)} \tag{1}$$

$$\vec{D}_G(x,y,b;g) = max\{\beta \mid (y+\beta g_y, b-\beta g_b) \in P_G(x)\} \tag{2}$$

$$P_G(x) = \{(y,b) \mid x \to (y,b),\ \forall t = 1,\dots,T\} \tag{3}$$

$$GML_t^{t+1} = GEC_t^{t+1} \times GTC_t^{t+1} \tag{4}$$

$$g = (g_y, g_b) = (y,-b) \tag{5}$$

P_G(x) defines all feasible output combinations for input x; inputs are labor, capital, and energy; the desirable output is gross regional product, the undesirable output is SO2; g=(g_y,-g_b) increases desirable outputs while reducing undesirable ones. The GML decomposes into green efficiency change (GEC) and green technological progress (GTC). The core explanatory variable is the market-oriented allocation efficiency of data factors. After computing the Pythagorean fuzzy hybrid weighted distance (PFHWD), the TOPSIS closeness formula integrates the distances to obtain the efficiency value (Equation (6)):

$$C_{it} = \frac{D_{it}^-}{D_{it}^+ + D_{it}^-} \tag{6}$$

C_it in [0,1] is the efficiency; D_it^± are weighted distances to the ideal solutions. In regressions the inverse hyperbolic sine transform asinhD mitigates skewness and accommodates zeros, with Defficiency as a robustness replacement. The model includes only environmental regulation intensity (lnER) and the one-period-lagged GTFP as controls, excluding lnGDP and lnFDI based on collinearity diagnostics: adding them makes lnGDP significantly negative, lnFDI insignificant, and shifts lnER from significant to insignificant. Retaining only lnER more cleanly identifies the net effect [16][17].

A three-level framework—baseline, dynamic, and spatial: a static panel (pooled OLS, FE, RE) for direction (Equation (7)), system GMM for endogeneity and dynamics (Equation (8)), and a spatial Durbin model for regional interaction (Equation (9)):

$$GTFP_{it} = \alpha + \beta_1 asinhD_{i,t-1} + \beta_2 \ln ER_{it} + \mu_i + \varepsilon_{it} \tag{7}$$

$$GTFP_{it} = \alpha + \rho GTFP_{i,t-1} + \beta_1 asinhD_{i,t-1} + \beta_2 \ln ER_{it} + \mu_i + \varepsilon_{it} \quad (8)$$

$$GTFP_{it} = \rho \sum_j w_{ij}\, GTFP_{jt} + \beta X_{it} + \theta \sum_j w_{ij}\, X_{jt} + \mu_i + \varepsilon_{it} \quad (9)$$

GTFP_it is green productivity of city i in t; asinhD_{i,t-1} is the lagged transformed allocation efficiency; lnER_it is log environmental regulation; μ_i the individual effect; ε_it the error; ρ is the spatial autoregressive coefficient; θ the spatial-lag coefficient; w_ij an element of the row-standardized Queen contiguity matrix. Specification is chosen by F, LM, and Hausman tests. System GMM instruments endogenous regressors with higher-order lags; validity is assessed by AR(2) and Hansen tests. Effects are decomposed into direct, indirect, and total via partial derivatives.

3.2 Data Sources and Processing

Data are a panel of 14 prefecture-level cities in Hunan over 2010–2023, from the Hunan Statistical Yearbook, China City Statistical Yearbook, municipal bulletins, EPS, and CNRDS. Linear interpolation fills consecutive missing values, nearest-neighbor fills endpoints, and isolated gaps use means. GTFP is winsorized at 1%/99%. LLC and IPS tests assess stationarity; first differencing handles unit roots.

4 Measurement and Spatiotemporal Evolution

The measurement targets 14 cities and 6 indicators over 2010–2023 in four steps. First, log-smoothing and extreme-value normalization (Equation (10)):

$$r_{tij} = \frac{x_{tij} - \min_i x_{tij}}{\max_i x_{tij} - \min_i x_{tij}} \quad (10)$$

r_tij is the normalized value; when max equals min, the column is set to 0.5. Second, normalized values map to Pythagorean fuzzy numbers (Equation (11)):

$$\mu_{tij} = r_{tij}, \nu_{tij} = \sqrt{1 - \mu_{tij}^2} \quad (11)$$

μ_tij is membership, ν_tij non-membership, with μ_tij^2+ν_tij^2<=1. Third, positive/negative ideal solutions from max/min membership (Equation (12)):

$$\mu_j^+ = \max_i \mu_{tij}, \mu_j^- = \min_i \mu_{tij} \quad (12)$$

Fourth, the PFHWD with entropy objective weight w_j (Equation (13)):

$$D_{it}^{\pm} = \sqrt{\sum_j w_j \left[(\mu_{tij} - \mu_j^{\pm})^2 + (\nu_{tij} - \nu_j^{\pm})^2 \right]} \quad (13)$$

D_it^± are weighted distances to the ideal solutions; substituting into Equation (6) yields the efficiency. The indicator and variable systems are shown in Tables 1 and 2.

Table 1. Measurement indicator system of green total factor productivity.

Category	Secondary Indicator	Specific Measurement	Data Source
Input	Labor, Capital, Energy	Urban employed persons (10,000 persons), Fixed asset investment (100 million yuan), Total energy consumption (10,000 tons of standard coal)	Hunan Statistical Yearbook, municipal statistical yearbooks
Desirable Output	Economic Benefit, Technological Innovation	Gross regional product (100 million yuan), Number of patent applications	Hunan Statistical Yearbook, China Industrial Economic Statistical Yearbook
Undesirable Output	Environmental Cost	Sulfur dioxide emissions (tons)	Municipal statistical yearbooks, Environmental statistical bulletins

Table 2. Description of main variables.

Type	Variable	Symbol	Description
Dependent Variable	Green Total Factor Productivity	GTFP	GTFP measured by the GML index
Core Explanatory Variable	Data Factor Market-Oriented Allocation Efficiency	asinhD/Defficiency	Inverse hyperbolic sine transform and original value of allocation efficiency, one-period lag
Control Variable	Environmental Regulation Intensity	lnER	Log of environmental regulation intensity

Table 3 reports the descriptive statistics. The efficiency shows a fluctuating decline-then-stabilize pattern without clear improvement: Changsha ranks first by a wide margin; Changde, Zhuzhou, and Hengyang form a second tier; Yueyang, Shaoyang and others a third tier; Huaihua, Loudi, and Xiangxi/Zhangjiajie lag. The pattern is 'single-pole-dominated, east-high-west-low.' The heatmap (Fig. 1) shows efficiency declined in most cities during 2011–2015 (early market construction), stabilized during 2016–2020, and slightly converged during 2021–2023. The Changsha-Zhuzhou-Xiangtan region is efficient but Changsha's radiation has not synchronously lifted Zhuzhou and Xiangtan, and western Hunan remains an efficiency depression—a typical core-periphery structure.

Table 3. Descriptive statistics of data factor market-oriented allocation efficiency.

Year	Mean	Std. Dev.	Min	Max
2010	0.3840	0.1415	0.2126	0.7646
2011	0.3561	0.1643	0.1663	0.8260
2012	0.3792	0.1562	0.1745	0.7989
2013	0.3829	0.1657	0.1815	0.8496
2014	0.4155	0.1582	0.2028	0.8301
2015	0.3637	0.1712	0.1725	0.8870
2016	0.3935	0.1674	0.2055	0.8898
2017	0.3876	0.1703	0.1787	0.8963
2018	0.3884	0.1672	0.1918	0.8986
2019	0.3753	0.1679	0.1810	0.8978
2020	0.3766	0.1634	0.1933	0.8877
2021	0.3752	0.1600	0.1848	0.8814
2022	0.3767	0.1585	0.1842	0.8730
2023	0.3853	0.1558	0.1856	0.8715

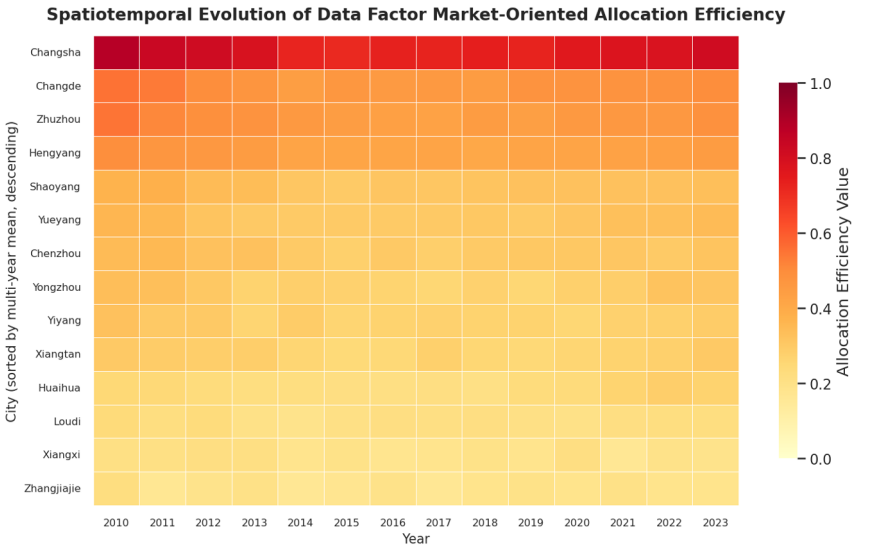


Fig. 1. Spatiotemporal evolution heatmap of data factor market-oriented allocation efficiency.

From 2011 to 2023 the provincial GTFP mean fluctuated between 1.02 and 2.74 without a clear trend, with wide city dispersion. The global Moran's I (Table 4) fluctuates between positive and negative: significantly negative in 2011 (single-pole staggered pattern), highly significantly positive in 2017 (agglomeration), significantly positive at 5% in 2020, and marginally significantly negative in 2023 (differentiation resurging). The local Moran scatter for 2023 shows most cities in the LL and HL quadrants, indicating intensified spatial differentiation and a persistent core-periphery gap.

Table 4. Global Moran's I of GTFP in Hunan Province (2011–2023).

Year	Moran's I	Z Value	P Value	Significance
2011	-0.3249	-1.5655	0.037	**
2012	0.0296	0.6771	0.232	
2013	-0.1217	-0.3194	0.406	
2014	0.0298	0.6462	0.226	
2015	-0.1586	-0.4451	0.371	
2016	-0.0690	0.1008	0.371	
2017	0.4079	3.2339	0.004	***
2018	-0.2337	-1.2050	0.093	*
2019	0.0846	1.0365	0.159	
2020	0.2378	2.4334	0.029	**
2021	-0.0274	0.3220	0.347	
2022	-0.2317	-1.1641	0.095	*
2023	-0.2801	-1.4604	0.053	*

Note: *, **, *** denote significance at the 10%, 5%, 1% levels, respectively. Row-standardized Queen contiguity matrix.

5 Empirical Results

5.1 Baseline and System GMM

Table 5. Baseline regression and system GMM estimation results.

Variable	Model (1) FE	Model (2) SYS-GMM	Model (3) FE	Model (4) SYS-GMM
L.GTFP_w	—	0.002 (0.942)	—	0.002 (0.937)
L.asinhD	7.374 (0.135)	4.570*** (0.000)	—	—
L.Defficiency	—	—	6.911 (0.121)	4.125*** (0.000)
lnER	-1.642*** (0.007)	-1.993*** (0.001)	-1.655*** (0.006)	-1.998*** (0.001)
Constant	9.253** (0.018)	12.335*** (0.000)	9.415** (0.013)	12.481*** (0.000)
N	168	168	168	168
Groups	14	14	14	14
Within R^2	0.100	—	0.101	—
Wald χ^2/F value	4.65**	418.57***	4.64**	445.56***
AR(1) p-value	—	0.000	—	0.000
AR(2) p-value	—	0.456	—	0.512
Hansen p-value	—	0.215	—	0.198

Note: p-values in parentheses; ***, **, * denote significance at the 1%, 5%, 10% levels, respectively. Models (1) and (3) are two-way fixed effects models; Models (2) and (4) are two-step system GMM; AR(2) and Hansen report corresponding test p-values.

After 1% winsorization, GTFP_w has mean 1.54 (SD 1.10); L.asinhD has mean 0.35 (SD 0.14), with L.Defficiency correlating 0.999, validating the asinh transform; lnER has mean 6.50. Static panel estimates (Table 5, Models 1 and 3) give L.asinhD a coefficient of 7.374 but insignificant at the 13.5% level (p = 0.135); lnER is -1.642 and significant at 1%, consistent with short-term compliance-cost inhibition; within-group

R2 is 0.100. The direction is as expected but significance is insufficient, motivating the dynamic panel. System GMM (Table 5, Models 2 and 4) gives the lagged allocation efficiency a coefficient of 4.570, significant at 1%: a one-unit rise in the previous period's efficiency raises current GTFP by about 4.57 units. Replacing with L.Defficiency keeps sign and significance (4.125, $p < 0.01$), confirming robustness. The lag structure implies a transmission cycle of about one year. Environmental regulation's significantly negative coefficient is more consistent with the compliance-cost hypothesis than the Porter hypothesis [18]. AR(2) and Hansen do not reject the null, indicating valid instruments.

5.2 Robustness Tests

Four robustness tests (Table 6) support the core conclusion. (1) Extending the lag to two periods makes L.asinhD insignificant (1.038, $p = 0.611$) while L2.GTFP_w is significant at 5%—consistent with a one-year transmission window. (2) Replacing asinh with L.Defficiency yields 4.125 ($p < 0.01$). (3) Adding lnFDI raises the core coefficient to 7.778 ($p < 0.01$). (4) Dropping lnER keeps it at 4.996 ($p < 0.01$).

Table 6. Robustness test results (system GMM estimation).

Variable	Model (1) 2nd Lag	Model (2) Alt. Measure	Model (3) Add lnFDI	Model (4) Simplified
L.GTFP_w	0.008 (0.907)	0.002 (0.937)	-0.001 (0.991)	0.032* (0.062)
L2.GTFP_w	0.061** (0.034)	—	—	—
L.asinhD	1.038 (0.611)	—	7.778*** (0.000)	4.996*** (0.000)
L.Defficiency	—	4.125*** (0.000)	—	—
Constant	-2.495** (0.011)	-1.998*** (0.001)	—	—
lnFDI	—	—	1.156** (0.017)	—
N	16.513*** (0.004)	12.481*** (0.000)	9.869*** (0.000)	-0.136 (0.542)
Wald χ^2	154	168	168	168
AR(2) p-value	592.83***	445.56***	495.56***	86.90***
Hansen p-value	0.312	0.512	0.423	0.587
Hansen p-value	0.185	0.198	0.243	0.317

Note: Model (1) uses the second-order lag of the core variable; Model (2) replaces L.asinhD with L.Defficiency; Model (3) adds lnFDI; Model (4) excludes lnER. p-values in parentheses; significance notation as in Table 5.

5.3 Spatial Durbin Model and Effect Decomposition

OLS-residual spatial diagnostics: LM-Lag = 5.638 (p = 0.018) and LM-Error = 4.933 (p = 0.026), both significant at 5%, justifying the SDM. The SDM (Table 7) gives ρ = 0.211 (p = 0.690), positive but insignificant; spatial-lag coefficients W×asinhD (p = 0.499) and W×lnER (p = 0.837) are also insignificant, indicating weak spatial interaction in this sample. Because the spatial multiplier (I-ρW)^-1 chains feedback, point estimates cannot be read as marginal effects; Table 8 reports the effect decomposition.

Table 7. Spatial Durbin model estimation results (point estimate coefficients).

Parameter	Coefficient
ρ (Spatial autoregressive)	0.2109
asinhD (Main coefficient β_1)	0.0773
lnER (Main coefficient β_2)	0.1755
W×asinhD (Spatial lag θ_1)	-4.0267
W×lnER (Spatial lag θ_2)	-0.8305

Note: Dependent variable GTFP_w; row-standardized Queen contiguity matrix; N = 168, R2 = 0.079. SDM point estimates are not used for direct inference; spatial effects are reported in Table 8.

Following LeSage and Pace [21], the partial-derivative method decomposes total effects into direct, indirect, and total (Table 8). For allocation efficiency, the direct effect is 0.098 (weak positive local impact) and the indirect effect -5.082; the negative indirect effect is a preliminary finding suggesting competitive pressure on neighbors, consistent with the single-pole structure in which Changsha may siphon surrounding cities [19]; the total effect is -4.984, read with caution. For environmental regulation, the direct effect is 0.222, indirect -1.006 and total -0.783; Liu and Huang note that high-pollution FDI tends to enter weakly regulated regions via joint ventures [20], so neighbors' stricter regulation may push such enterprises locally and suppress local GTFP.

Table 8. Effect decomposition of the spatial Durbin model.

Variable	Direct Effect	Indirect Effect	Total Effect
L.asinhD	0.098	-5.082	-4.984
lnER	0.222	-1.006	-0.783

6 Discussion and Conclusions

Results indicate data factor marketization influences regional sustainability through resource optimization and green technological progress, with the lagged efficiency acting via the innovation channel. The system-GMM–SDM combination captures both temporal transmission (one-year absorption cycle) and cross-sectional interaction; the weak spatial significance cautions that spatial dependence is not always strong. For policy, the lagged effect calls for patience—green dividends materialize

over roughly a year; the potential negative spillover underscores regional coordination; and short-term environmental regulation inhibition suggests managing compliance costs via market-based incentives. Using panel data of 14 Hunan prefecture-level cities (2010–2023), this paper finds that one-period-lagged data factor allocation efficiency significantly and robustly drives GTFP, transmitted mainly through green technological progress and concentrated within an approximately one-year cycle. The SDM yields a suggestive but inconclusive pattern: local efficiency gains may exert competitive pressure on neighbors, possibly a siphon-type dynamic consistent with Hunan's single-pole structure. Environmental regulation shows a short-term inhibitory effect. The contribution is connecting data factor marketization to sustainability via the GTFP channel. Limitations: the 14-city Hunan sample needs cross-provincial comparisons; the efficiency indicator system is constrained by data availability; several SDM coefficients are insignificant and the negative indirect effect is preliminary, calling for alternative spatial specifications (SEM, SLM, SLX), multiple weight matrices, and extended series in future research. Acknowledgments: the author thanks Hunan University and acknowledges data from the Hunan Statistical Yearbook, China City Statistical Yearbook, EPS, and CNRDS databases. Funding: none. Author Contributions: Y.D. conducted all aspects. Conflicts of Interest: none.

References

1. Shi, D.; Sun, G. Data Factors and New Quality Productive Forces: From the Perspective of Enterprise Total Factor Productivity. Econ. Theory Bus. Manag. 2024, 44, 12-30. (In Chinese).
2. Cai, Y.; Fu, Y. Technology Effect and Structure Effect in Total Factor Productivity Growth: Measurement and Decomposition Based on China's Macro and Industrial Data. Econ. Res. J. 2017, 52, 72-88. (In Chinese).
3. Yang, Y.; Wang, L.; Liao, Z. Market-Oriented Allocation of Data Factors and Regional Economic Development: From the Perspective of Data Trading Platforms. Soc. Sci. Res. 2021, 38-52. (In Chinese).
4. Liu, X.; Liu, Q. Research on the Reform of Factor Market-Oriented Allocation. Macroeconomics 2019, 34-47. (In Chinese).
5. Sheng, B.; Liu, Y. Measurement and Spatial Differentiation Characteristics of China's Digital Economy Development Index. Nanjing J. Soc. Sci. 2022, 43-54. (In Chinese).
6. Ren, B.; Wen, F. Judgment Criteria, Determinants and Realization Approaches of China's High-Quality Development in the New Era. Reform 2018, 5-16. (In Chinese).
7. Huang, Q.; Hu, J.; Chen, X. Environmental Regulation and Green Total Factor Productivity: A Dilemma or a Win-Win? China Popul. Resour. Environ. 2018, 28, 140-149. (In Chinese).
8. Li, B.; Qi, Y.; Li, Q. Fiscal Decentralization, FDI and Green Total Factor Productivity: An Empirical Test Based on Dynamic GMM of Panel Data. J. Int. Trade 2016, 119-129. (In Chinese).
9. Wei, M.; Li, S. Measurement of China's Economic High-Quality Development Level in the New Era. J. Quant. Technol. Econ. 2018, 35, 3-20. (In Chinese).
10. Shi, B.; Ren, B. Measurement and Analysis of China's Inter-Provincial Economic High-Quality Development. Econ. Probl. 2018, 1-6. (In Chinese).

11. Ge, H.; Wu, F. Digital Economy Empowering High-Quality Economic Development: Theoretical Mechanism and Empirical Evidence. Nanjing J. Soc. Sci. 2021, 24-33. (In Chinese).
12. Fan, H.; Wu, T. Can Digitalization Promote Economic Growth and High-Quality Development? Empirical Evidence from China's Provincial Panel Data. J. Manag. 2021, 34, 36-53. (In Chinese).
13. She, S.; Wang, Q.; Zhang, A. Technological Innovation, Industrial Structure and Urban Green Total Factor Productivity. Econ. Manag. Res. 2020, 41, 44-61. (In Chinese).
14. Cui, X.; Lin, M. How Does FDI Affect Enterprises' Green Total Factor Productivity? An Empirical Analysis Based on Malmquist-Luenberger Index and PSM-DID. Bus. Manag. J. 2019, 41, 38-55. (In Chinese).
15. Ou, J.; Xu, C.; Liu, Y. Measurement of Economic High-Quality Development Level Based on the 'Five Development Concepts'. Econ. Geogr. 2020, 40, 77-86. (In Chinese).
16. Zhang, Y.; Luo, E. Environmental Regulation, Technological Innovation and Economic Growth: A Comparative Analysis. West. Econ. Manag. Forum 2019, 30, 32-39. (In Chinese).
17. Xiong, Y. Relationship between Environmental Regulation and Economic Growth Based on Inter-Provincial Data. China Popul. Resour. Environ. 2011, 21, 126-131. (In Chinese).
18. Zhang, C.; Li, J.; Yuan, Z. The Impact of Environmental Regulation Intensity on Green Innovation Efficiency: The Moderating Effect of Fiscal Pressure. Technoecon. Manag. Res. 2024, 101-107. (In Chinese).
19. Yao, C.; Hu, H. Digital Economy, Innovation Resource Flow and Regional Innovation Capacity Improvement: A Spatial Durbin Model Study. J. Southwest Minzu Univ. (Hum. Soc. Sci. Ed.) 2023, 44, 106-115. (In Chinese).
20. Liu, B.; Huang, J. Research on the Impact of FDI Entry Modes on Regional Green Technology Innovation Efficiency. Contemp. Financ. Econ. 2017, 89-98. (In Chinese).
21. LeSage J, Pace R K. Introduction to Spatial Econometrics. Boca Raton: CRC Press, 2009.

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