Digital economy configurations and urban green total factor productivity growth: A dynamic QCA analysis

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Abstract. This study examines how combinations of digital-economy conditions relate to urban green total factor productivity growth. Using a panel of Chinese prefecture-level and above cities, annual green productivity growth was estimated with an undesirable-output SBM-GML model. Dynamic qualitative comparative analysis was then applied to configurations of digital networks, talent, industry, finance, innovation and adoption. No single digital condition was sufficient to explain high growth. Instead, distinct combinations led to the same outcome. The identified configurations formed two types, digital finance support and digital innovation synergy, whose stability over time and applicability across cities differed. By separating the supply, output and access dimensions of the digital economy and combining configurational analysis with longitudinal consistency tests, the study provides configurational evidence on the relationship between digitalisation and green productivity growth under heterogeneous urban conditions.

Keywords: Digital economy; green total factor productivity; SBM-GML; dynamic QCA; configurational paths

1. Introduction

Urban green transition requires higher productive efficiency with lower resources and environmental costs. Green total factor productivity (GTFP) incorporates undesirable outputs into productivity assessment [1]. This study asks which combinations of digital conditions are associated with better resource allocation and urban green productivity growth when digital technologies enter production and service activities.

Goldfarb and Tucker showed that digital technologies reduce search, replication, transportation, tracking and verification costs [2]. Lyu et al. reported positive and spatial spillover effects of the digital economy on GTFP, with green technological progress as an important channel [3]. Qian et al. explained this relationship through economic scale, industrial structure and technological innovation [4]. Evidence from China's national big-data pilot zones further indicates that the effects vary with urban location, resource endowment and size [5]. These studies imply that the environmental gains from digitalisation depend on local development conditions. How cities with different network, labour and industrial foundations combine digital resources therefore merits closer examination.

Configurational research considers the joint effects of multiple conditions and the possibility that different combinations lead to the same outcome [6,7]. Previous fuzzy-set qualitative comparative analyses have identified multiple links between the digital economy and GTFP [8,9]. This study distinguishes network supply from user access and specialised labour input from digital knowledge output. It then uses a panel set-theoretic framework to assess temporal stability and cross-city heterogeneity [10, 11].

Input-output data for 267 cities from 2018 to 2023 were used to estimate a green productivity growth index. Dynamic qualitative comparative analysis (QCA) was conducted for annual outcomes from 2019 to 2023. The conditions cover digital network support, talent supply, industrial development, financial services, technological innovation and technology adoption. The analysis links the meaning of these conditions with configurational paths, between-year consistency and within-city consistency.

2. Materials and methods

2.1. Outcome: green total factor productivity based on SBM-GML

Green total factor productivity growth was estimated using a slacks-based measure (SBM) model with undesirable outputs and the global Malmquist-Luenberger (GML) index. The SBM model accounts for input and output slacks [12], whereas the directional distance function and the global production possibility set incorporate pollution emissions and enable intertemporal comparison [1,13]. In Eq. (1), D^G denotes the global directional distance function, and x, y and b denote inputs, desirable outputs and undesirable outputs, respectively. A GML value above 1 indicates growth relative to the previous period, whereas a value below 1 indicates decline.

$$GML^{t,t+1} = \frac{1 + D^G(x^t, y^t, b^t)}{1 + D^G(x^{t+1}, y^{t+1}, b^{t+1})} \quad (1)$$

Inputs comprised labour, capital, energy and land. Real GDP was the desirable output, while industrial wastewater, sulphur dioxide and smoke or dust emissions were undesirable outputs. Urban built-up areas were used as a proxy for land input and represented developed construction space. The indicators are listed in Table 1.

2.2. Condition variables and construction

The digital economy encompasses information processing, network connectivity and related economic activities supported by digital technology, which affect production and services by reducing information and transaction costs [2]. Following previous configurational research [8], six conditions were defined to represent connection infrastructure, specialised labour, service output, financial services, knowledge output and user access. Table 1 lists their indicators.

Digital network support (NET) measures base-station supply density and technological structure. Digital talent supply (TAL) measures specialised labour input and concentration. Digital industry development (IND) uses telecommunications revenue intensity as a proxy for local communications service output and is therefore limited to the communications service industry.

Digital financial services (FIN) use the coverage breadth and usage depth of the Peking University Digital Financial Inclusion Index [14] to measure service reach and use. Digital technological innovation (INN) measures knowledge output through the intensity of digital invention patent applications and grants. Digital technology adoption (APP) measures access and the basis for service use through broadband and mobile-phone user intensity. NET and APP thus represent supply and access, whereas TAL and INN represent labour input and knowledge output. Interpretations are restricted to these measurement definitions.

$$z_{ijt} = \frac{x_{ijt} - min\ x_j}{max\ x_j - min\ x_j}, \quad C_{kit} = \frac{z_{1,it} + z_{2,it}}{2} \quad (2)$$

Table 1. Measurement of the outcome and condition variables.

Variable type	Variable or dimension	Indicator
Outcome	Inputs	Labour: employees in urban units at year end; capital: fixed-capital stock; energy: total energy consumption; land: urban built-up area
	Outcome Desirable output	Real GDP at constant prices
	Outcome Undesirable outputs	Industrial wastewater, sulphur dioxide, and smoke or dust emissions
Condition	Digital network support (NET)	Mobile communication base stations per 10,000 people; share of 4G base stations

Variable type	Variable or dimension	Indicator
	Condition Digital talent supply (TAL)	Employment in information transmission, computer services and software / total employment; sector employment per 10,000 people
	Condition Digital industry development (IND)	Telecommunications revenue / GDP; telecommunications revenue per capita
	Condition Digital financial services (FIN)	Coverage breadth and usage depth of digital financial inclusion
	Condition Digital technological innovation (INN)	Digital-economy invention patent applications and grants per 10,000 people
	Condition Digital technology adoption (APP)	Broadband subscribers and mobile-phone users per 100 people

All component indicators were positively oriented. Digital patent intensity was transformed into $\ln(1 + x)$, after which every indicator was range-standardised over the full sample. The two indicators within each condition received equal weights, as shown in Eq. (2) and Table 1.

2.3. Dynamic QCA

Configurational analysis explains outcomes through combinations of conditions and permits multiple paths to the same outcome [6,7]. Fuzzy-set qualitative comparative analysis (fsQCA) calibrates variables as set memberships and identifies set relations through necessity analysis, truth tables and logical minimization [7,15]. To examine temporal stability and case heterogeneity beyond cross-sectional configurations, García-Castro and Ariño proposed a panel framework that separates pooled, between-group and within-group relations [10]. Bhattacharya subsequently detailed the analytical procedure [11]. This study follows that dynamic QCA framework.

The six conditions and annual GML values were converted to memberships between 0 and 1 by direct calibration [7,15]. Fixed values near the 5th, 50th and 95th percentiles of the full sample served as the anchors for full non-membership, crossover and full membership of each condition. For the outcome, the two outer anchors were the 5th and 95th percentiles, and the crossover was fixed at GML = 1 to distinguish growth from decline. The case-frequency, raw-consistency and proportional reduction in inconsistency (PRI) thresholds were 5, 0.80 and 0.65, respectively. Intermediate solutions were used as the main results and parsimonious solutions as supporting comparisons [6].

Cities were the cases and years were the temporal clusters. Pooled consistency covered all observations, between-group consistency described annual cross-sectional relations, and within-group consistency described longitudinal relations within each city from 2019 to 2023[10,11]. Coverage was also reported. Robustness tests increased the consistency and case-frequency thresholds and changed the calibration anchors.

2.4. Data and sample

The sample contained 1,602 observations for 267 prefecture-level and above cities from 2018 to 2023. Annual GML compared each year with the preceding year. Because data for 2017 were unavailable, 2018 served only as the base period for the 2019 index. Dynamic QCA therefore used 1,335 observations from 2019 to 2023.

Input-output data were obtained from the China City Statistical Yearbook, China Urban Construction Statistical Yearbook and municipal statistical bulletins. Digital finance data came from

the Peking University Digital Financial Inclusion Index [14]. The remaining conditions were constructed from collected data on base stations, telecommunications, employment and digital patents. Data were matched by city code and year, and no values were missing for the six conditions or annual GML in the final sample.

3. Results

3.1. Calibration

Table 2 reports the calibration anchors. Condition anchors were determined once from the full sample to maintain a common set standard across years. The annual GML crossover was fixed at 1, so that outcome membership represented green productivity growth relative to the previous year.

Table 2. Calibration anchors for baseline analysis.

Variable	Full non-membership	Crossover	Full membership
NET	0.05555882	0.23173955	0.44564419
TAL	0.02577469	0.04501314	0.21518942
IND	0.03148955	0.04671463	0.09718645
FIN	0.22457141	0.45598900	0.72585415
INN	0.01370712	0.08770952	0.52819170
APP	0.21809939	0.33684301	0.49289524
GML	0.98112608	1.00000000	1.12148291

3.2. Necessity analysis

Using 0.90 as the necessity-consistency criterion [7], neither the six conditions nor their negations met the threshold (Table 3). The highest consistency was 0.748 for ~TAL, followed by 0.746 for ~IND, while the presence of FIN reached 0.703. No individual condition was necessary for high green productivity growth, which warranted analysis of their combinations.

Table 3. Necessity analysis for high green productivity growth.

Condition	Consistency when present	Consistency when absent
Digital network support (NET)	0.669	0.681
Digital talent supply (TAL)	0.633	0.748
Digital industry development (IND)	0.625	0.746
Digital financial services (FIN)	0.703	0.649
Digital technological innovation (INN)	0.627	0.709
Digital technology adoption (APP)	0.681	0.673

3.3. Sufficiency analysis

The baseline intermediate solution identified three paths, with individual consistencies of 0.897-0.939. Overall consistency, PRI and coverage were 0.887, 0.681 and 0.599, respectively (Table 4). Together, the paths covered 59.9% of outcome membership. The table retains condition states from the intermediate solution. Because the parsimonious solution had several alternatives, core and peripheral conditions were not uniformly assigned.

Configuration 1 was ~IND×FIN: non-high local communications service output intensity combined with high digital financial services and corresponded to high green productivity growth. Its raw and unique coverage values were 0.546 and 0.203, respectively, both higher than those of the other paths. This path therefore covered a broader share of the sample and had a larger independent explanatory range.

Configuration 2 was ~NET×FIN×INN×APP. Under non-high network supply, high digital finance, digital innovation and communications access jointly corresponded to high growth. Its consistency of 0.939 was the highest among the three paths, while its raw coverage was 0.325. The set relation was highly consistent but applied to a narrower range of cases.

Configuration 3 was ~TAL×FIN×INN×APP. Its distinguishing condition relative to Configuration 2 was non-high digital talent supply, while high digital finance, innovation and communications access remained common conditions. Consistency was 0.926 and raw coverage was 0.366, indicating that the shared combination also occurred in cities where specialised labour quantity did not enter the high set.

Configuration 1 was classified as the digital finance support type. Configurations 2 and 3 shared FIN×INN×APP and were classified as the digital innovation synergy type. The latter contained two contexts distinguished by network or talent supply; Table 4 therefore reports the two subpaths and their fit statistics separately.

Table 4. Configurations for high green productivity growth.

Condition or statistic	Configuration 1	Configuration 2	Configuration 3
Digital network support (NET)		⊗	
Digital talent supply (TAL)			⊗
Digital industry development (IND)	⊗		
Digital financial services (FIN)	●	●	●
Digital technological innovation (INN)		●	●
Digital technology adoption (APP)		●	●
Consistency	0.897	0.939	0.926
PRI	0.690	0.709	0.704
Raw coverage	0.546	0.325	0.366
Unique coverage	0.203	0.011	0.022
Overall consistency		0.887	
Overall PRI		0.681	
Overall coverage		0.599	

Note: ● indicates the presence of a condition, ⊗ its absence, and a blank that the condition is unrestricted in the path. The symbols report condition states only. The tilde (~) denotes set negation and × denotes conjunction. Raw and unique coverage are reported for each path.

3.4. Between-group consistency and coverage

Annual between-group consistency exceeded 0.80 for all three paths from 2019 to 2023 (Figure 1a). Their set relations with high growth were therefore supported in each year rather than concentrated in a single period. Configuration 1 declined from 0.947 in 2019 to 0.863 in 2022 and recovered to 0.927 in 2023. Configurations 2 and 3 ranged from 0.907 to 0.967 and from 0.889 to 0.955, respectively, and varied less than Configuration 1.

Coverage for all three paths fluctuated but ended above its initial level. It rose from 0.313 to 0.654 for Configuration 1, from 0.234 to 0.383 for Configuration 2 and from 0.255 to 0.442 for Configuration 3 (Figure 1b). Thus, the share of high-growth outcome membership covered by each path generally increased. Configuration 1 increased most, indicating broader coverage of the digital finance support type later in the sample period.

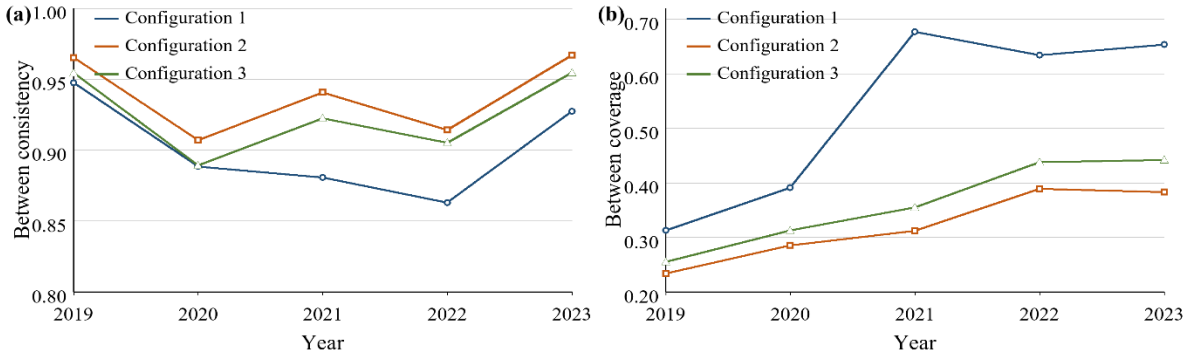


Figure 1. Annual between-group consistency and coverage of the three configurations.

3.5. Within-group consistency

Within-group consistency assesses whether a path-outcome relation holds across years within the same city [10,11]. Mean values for the three paths were 0.911, 0.942 and 0.938, and the proportions of cities reaching 0.80 were 81.3%, 89.1% and 87.6%, respectively (Table 5). Longitudinal relations were consistent for most cities. Configurations 2 and 3 had higher means and qualifying proportions than Configuration 1, indicating that the digital innovation synergy type was stable over time in more cities.

For Configuration 3, Beijing had zero path membership in all five years. The denominator of its within-group consistency was therefore zero, leaving 266 valid cities; an undefined value did not indicate low consistency. Some cities still fell below 0.80 for each path, which indicates differences in local applicability. A cross-sectional relation in every year does not imply equal longitudinal fit for every city.

Table 5. Summary of within-city consistency for high-growth paths.

Path	Valid cities	Mean	Median	Minimum	Cities ≥0.80	Share ≥0.80
Configuration 1	267	0.911	0.983	0.365	217	81.3%
Configuration 2	267	0.942	1.000	0.518	238	89.1%
Configuration 3	266	0.938	1.000	0.538	233	87.6%

3.6. Robustness tests

Raising the raw-consistency threshold from 0.80 to 0.85 or the case-frequency threshold from 5 to 10 left the three baseline intermediate solutions and their fit statistics unchanged. When condition anchors were changed to the 10th, 50th and 90th percentiles, and outcome anchors to the 10th percentile, 1 and the 90th percentile, the solutions became simpler. Nevertheless, the main structures ~IND×FIN and FIN×INN×APP remained. Overall consistency, PRI and coverage were 0.817, 0.668 and 0.627, respectively. The two configurational types were stable under threshold changes, although the detailed combinations showed some sensitivity to calibration.

4. Discussion

All three paths in Table 4 contained high digital financial services. Equipment renewal and digital technology adoption usually require upfront capital. Access to suitable financial services may therefore affect whether a technical plan becomes an actual investment. The breadth and depth dimensions of digital finance [14] measure this reach and use. The following sections discuss the digital finance support and digital innovation synergy types, using city practices during the study period to illustrate plausible processes.

4.1. Digital finance support

Chuzhou in 2023 conformed to the digital finance support configuration. Its Xinyidai platform provided credit and guarantee services and arranged online bank-enterprise matching for photovoltaic, automotive and equipment manufacturing, and new-energy battery industries [16]. The case shows how a digital platform can connect financing to the real economy without relying on high local communications-industry output. For firms seeking equipment renewal, access to an appropriate financial product and completion of financing are more directly relevant to investment than the scale of local telecommunications revenue.

This path combined ~IND and FIN. IND measured telecommunications revenue intensity, whereas FIN measured the reach and use of digital financial services. The two conditions therefore represented different economic activities. Goldfarb and Tucker's analysis of lower search, tracking and verification costs [2] helps explain how digital platforms may reduce information-identification and matching costs between banks and firms. Better financing conditions can enable firms to purchase equipment and digital services for energy-saving retrofits. Lyu et al. also linked digital technological

progress to green productivity [3]. Figure 2 therefore interprets this configuration as a setting in which digital finance supports technology adoption under non-high local communications service output intensity and is associated with green productivity growth. Local communications output and firms' access to digital services should be considered separately.

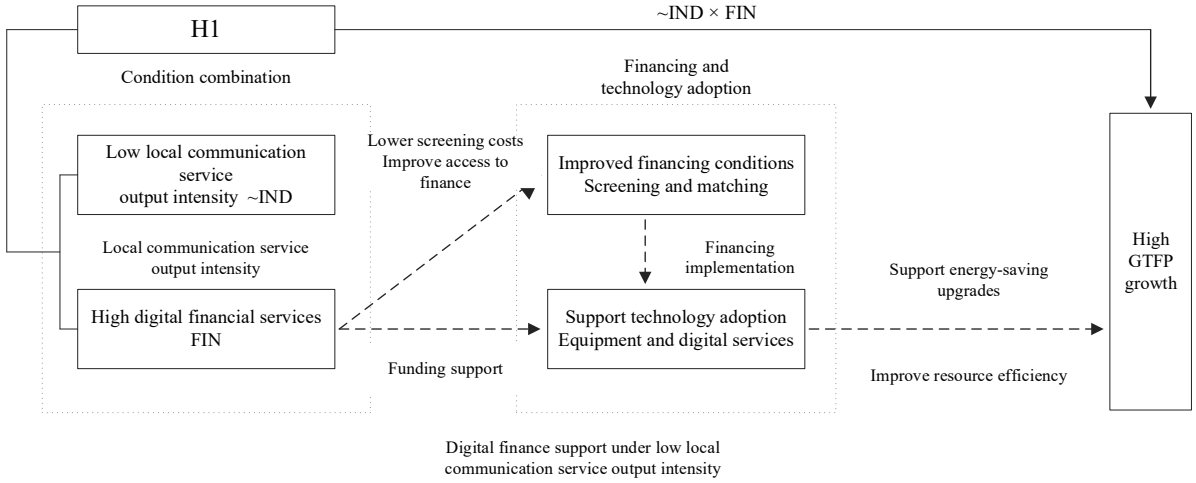


Figure 2. Configuration and interpretive links of the digital finance support path.

Note: Solid lines show configurational relations; dashed lines show interpretive links based on cases and prior studies.

4.2. Digital innovation synergy

Ezhou and Zhongshan in 2023 conformed to Configurations 2 and 3, respectively. Ezhou Iron and Steel integrated operating data from energy equipment and pipelines into a big-data energy management system for tracking consumption and scheduling production. It combined the system with automated steelmaking and process optimization to improve energy use [17]. This case illustrates that digital technology can contribute to energy saving when data are analyzed and used to adjust operations. Zhongshan supported manufacturing digitalization through digital loans and interest subsidies. In 2023, it brought partner banks, platform developers and firms together to match financing with transformation needs [18]. The two cases correspond to technology entering production and finance supporting implementation, providing practical context for FIN×INN×APP.

The digital innovation synergy type concerns the conditions under which technical solutions can be adopted. FIN provides finance for research, equipment and service purchases. INN captures digital patent output and represents knowledge available for development. APP captures communications access, which supports technology diffusion and digital service use. Pan et al. associated the digital economy with productivity through innovation [19], while Lyu et al. identified green technological progress as an important channel linking the digital economy to GTFP [3]. Figure 3 connects financial support, knowledge supply and access infrastructure to explain how they may jointly improve conditions for technology adoption and production optimization. Unlike the digital finance support type, this configuration explicitly includes digital knowledge output and communications access.

The two subpaths further distinguish supply quantity from conditions of use. In Configuration 2, non-high base-station supply coexisted with high communications access, showing that infrastructure quantity does not fully represent user access or service use. The Ezhou case likewise directs attention to whether data are used in production management. In Configuration 3, non-high information-service employment coexisted with high digital patent output, confirming that labour quantity and knowledge output are distinct dimensions. The ~NET and ~TAL conditions therefore define two urban contexts that combine separately with high FIN, INN and APP and correspond to high green productivity growth (Figure 3). Both paths had high between-year and within-city consistency. Cities may therefore organise technology adoption around existing finance, knowledge and access conditions rather than treat uniformly high digital inputs as a prerequisite.

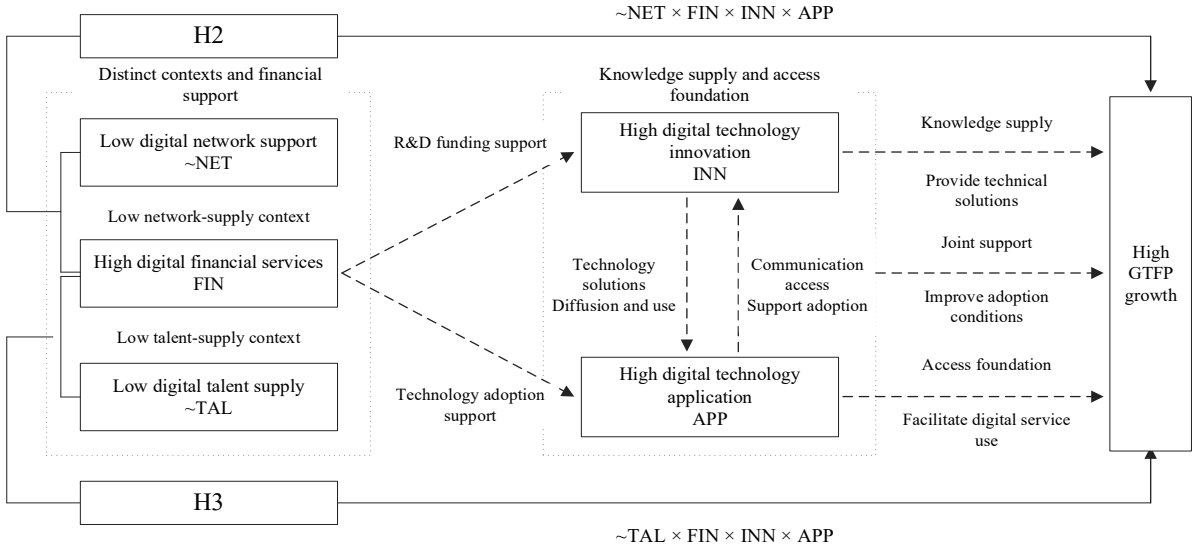


Figure 3. Configurations and interpretive links of the digital innovation synergy path.

Note: Solid lines show configurational relations; dashed lines show interpretive links based on cases and prior studies.

5. Conclusion

Two types of digital-economy configurations were associated with high green productivity growth. The digital finance support type combined high digital financial services with non-high local communications service output intensity. The digital innovation synergy type combined high digital finance, knowledge output and communications access under either non-high network supply or non-high digital talent quantity. Service reach, knowledge output and user access therefore differed conceptually from local communications output and specialised labour quantity. High growth did not require every digital condition to enter the high set.

All three paths maintained high consistency across years, but their longitudinal applicability varied among cities. Cities may improve digital financial services according to local conditions and coordinate finance, technology supply and communications access so that digital technologies enter production more effectively. City-level proxies cannot directly observe firms' use of finance or technology adoption, and the observation period was short. Future research could combine firm-level data with a longer window to examine the links between specific configurations and changes in green productivity.

Author contributions

The author was responsible for the study design, data preparation, empirical analysis, interpretation and manuscript preparation, and takes responsibility for the content of the manuscript.

Conflict of interest

The author declares no conflict of interest that could have influenced this study.

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