JEBIN Journal of Economics Business Industry
ISSN : 3025-0986
P-ISSN: 3025-0528
Volume 2, Number 1, 2024, pp 16-25
https://jurnaljepip.com/index.php/Jebin/index

New Quality Productive Forces in Taiwan Evidence from the Three New Economy Framework

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ABSTRACT
This study aims to measure the development of New Quality Productive Forces (NQPF) in Taiwan and explain their regional growth patterns, disparities, and spatial coordination dynamics under the Three New Economy framework. The study analyzes 19 Taiwanese administrative units from 2016 to 2022 using the super-efficiency MinDW Malmquist index, Dagum Gini decomposition, spatial conditional kernel density estimation, and spatial Markov chain analysis. Taiwan's NQPF increased moderately, with a national average index of 1.02, but growth remained uneven. Six regional growth patterns were identified, ranging from synchronous growth in major innovation corridors to incubation patterns in structurally constrained areas. Regional inequality widened after 2019 and formed a North high, East low spatial gradient, with between-region disparity contributing the largest share of total inequality. Spatial analysis further shows that backwash effects constrain low-tier regions, whereas medium-high regions such as Taichung and Kaohsiung function as potential spread transmitters. This study extends NQPF literature by operationalizing the Three New Economy concept within an efficiency-based productivity framework and by integrating productivity, inequality, and spatial mobility analysis in a single empirical design. The findings suggest the need for innovation corridors, relay-region strengthening, and location-specific transformation strategies. The study is limited to available regional data for 2016–2022; future research should incorporate firm-level data and longer post-pandemic observations to refine causal interpretation.

Keywords: New Quality Productive Forces, Three New Economy, Malmquist Index, Regional Disparity, Spatial Markov Chain Analysis.

INTRODUCTION
Taiwan is widely recognized as one of the most innovation-oriented economies in East Asia. Its industrial structure is built on strong competitive advantages in semiconductors, information and communication technology, and precision manufacturing (Lyu et al., 2023). In the context of the Fourth Industrial Revolution, powered by artificial intelligence, cloud computing, and big data, Taiwan is undergoing a fundamental shift away from a conventional factor driven growth model toward one where technological innovation serves as the primary engine of productivity (Meng & Zhao, 2022).

The term new quality productive forces or NQPF describes a superior form of production that is rooted in revolutionary technological breakthroughs, integration of new industry ecosystems, and transformation of business paradigms through innovation (Guo et al., 2023). Consistent with the techno economic paradigm framework proposed by (Y. Liu et al., 2022), NQPF represents a practical expression of how new technology reshapes the economy in the digital era (H. Wang et al., 2021). In Taiwan, government initiatives such as the DIGI+ plan launched in 2017, the AI Taiwan Action Plan of 2018, the 5G Smart City program, and the Biotech Taiwan initiative reflect a clear commitment to fostering a new quality industry ecosystem grounded in endogenous innovation (NSTC, 2022).

Despite this progress, significant academic gaps remain in understanding how NQPF is spatially distributed, how it grows across different parts of Taiwan, and what dynamics drive regional convergence or divergence. Three specific questions remain unanswered (Directorate General of Budget Executive Yuan, Taiwan, 2022). The first is how NQPF is distributed and grows heterogeneously across Taiwan's administrative units. The second is whether spatial polarization is widening regional disparities in NQPF development. The third is the extent to which backwash and spread effects from technologically advanced regions influence productivity convergence or divergence across the country (Xu & Zhang, 2020).

This study makes three distinct contributions to the existing literature. The first contribution is the development of a NQPF measurement framework adapted specifically to Taiwan's institutional and industrial context, integrating the Three New Economy value added concept into an efficiency-based productivity model. The second contribution is the application of the super efficiency MinDW Malmquist model, which is methodologically more robust than conventional SBM models, to produce more accurate NQPF growth estimates at the administrative unit level. The third contribution is the first empirical analysis of the spatiotemporal polarization dynamics of NQPF in Taiwan using spatial conditional kernel density estimation and spatial Markov chains.

METHODOLOGY

Conceptual Framework: New Quality Productive Forces in Taiwan

This study defines NQPF as an advanced form of productivity rooted in disruptive technological innovation, concretely manifested through the Three New Economy. In the Taiwan context, the Three New Economy encompasses three dimensions (H. J. Liu & Sun, 2023). The first dimension is new industries, which includes advanced semiconductors, artificial intelligence, biotechnology, and renewable energy. The second dimension is new business models, which covers financial technology, digital platforms, and smart manufacturing powered by the Internet of Things. The third dimension is new economic patterns, which refers to data driven value chain transformation and the circular economy. The combined value added generated by these three dimensions forms the empirical basis for measuring NQPF in this study (Wu & Chen, 2021).

Theoretically, the study builds on (Fan et al., 2023) techno economic paradigm, which argues that every technological revolution fundamentally reorganizes the factors of production. In the era of artificial intelligence and cloud computing, NQPF reflects a qualitative shift in production (National Science and Technology Council, 2022)(H. J. Liu et al., 2020): labor moves toward high skill digital profiles, tools of production evolve into cyber physical systems, and the objects of work shift from natural resources to high value data assets (J. Wang & Guo, 2023).

The Measurement Model: Super Efficiency MinDW Malmquist

This study avoids the conventional SBM (Slacks Based Measure) model because it systematically underestimates efficiency values, a problem known as underestimation bias caused by its at frontier farthest distance property (H. J. Liu et al., 2020). Instead, we adopt the MinDW model, which stands for Minimum Distance to a Weak Frontier (Y. S. Chen & Lin, 2021). This model measures efficiency based on the closest distance to the weak production frontier, making it less sensitive to extreme outliers (J. Wang et al., 2023; Yu et al., 2023). The super efficiency MinDW formulation is:

$$S_{v(x_{ik},y_{rk})} = \max\left(\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{\beta_z^* e_i}{x_{ik}}}{1-\frac{1}{q}\sum_{r=1}^{q}\frac{\beta_z^* e_r}{y_{rk}}}\right) \tag{1}$$

$$\sum_{j=1}^{n}\lambda_j x_{ij} + \beta_z e_i \le x_{ik}, i = 1,2,\dots,m \tag{2}$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - \beta_z e_r \ge y_{rk}, r = 1,2,\dots,q, \lambda \ge 0 \tag{3}$$

In this formula, *n* is the number of decision-making units (DMUs), which are the administrative units; x_{ij}_and y_{rj} are respectively the inputs and outputs of DMU *j*; *m* and *q* are the number of input and output variables; λ and β are the proportional change coefficients for inputs and outputs; and S_v is the minimum distance function to the weak frontier (Chang et al., 2023; Sun et al., 2023).

Based on the MinDW model, we construct the Malmquist productivity index to measure the dynamic change in NQPF over time:

$$M_t^{t+1} = \frac{S_v^t\,(x^{t+1}, y^{t+1})}{S_v^t\,(x^t, y^t)} \times \frac{S_v^t\,(x^{t+1}, y^{t+1})}{S_v^{t+1}\,(x^t, y^t)} \tag{4}$$

This Malmquist index is then decomposed into two components. The first is the Technical Efficiency Change index (EC), which measures how much more efficiently an administrative unit is using its existing technology. The second is the Technical Change index (TC), which measures how much the technological frontier itself has advanced (Hu & Guo, 2022; Lee & Lee, 2022; Meng & Zhao, 2022).

$$M_t^{t+1} = \mathrm{EC} \times \mathrm{TC} \tag{5}$$

A value greater than 1.00 means NQPF is growing, while a value below 1.00 means it is declining.

Input and Output Indicators

Input Variables

The first category is Capital Input. The capital stock for each administrative unit is estimated using the Perpetual Inventory Method, following the approach adapted for Taiwan regional data by (Lin & Wang, 2022). The proxy used is the annual value of fixed asset investment, updated using the investment price index from Taiwan's Directorate General of Budget, Accounting and Statistics (DGBAS), with a depreciation rate of 9.6 percent per year (Wu & Chen, 2021) (C. Wang & Wang, 2023).

The second category is Labor Input, represented by the annual average sectoral workforce per administrative unit, sourced from the DGBAS Manpower Survey and weighted by the proportion of workers employed in Three New Economy sectors (Office, 2023) (Li et al., 2020).

The third category is Innovation Input, measured using sectoral research and development expenditure from the Science and Technology Statistical Abstract published by Taiwan's National Science and Technology Council (NSTC), which serves as a proxy for the intensity of innovation investment (Lin & Wang, 2022).

Output Variables

The first output variable is Innovation Output, measured by the number of granted patents (not just patent applications) per administrative unit, sourced from the Taiwan Intellectual Property Office (TIPO). Using granted patents rather than applications ensures that only commercially verified innovations are counted.

The second output variable is Three New Economy Value Added. Following the methodology (Xu & Zhang, 2020) of adapted for the Taiwan context, we calculate this value added using a sectoral adjustment coefficient, which is the ratio of Three New subsector value added to total sectoral value added, based on regional input output tables published by DGBAS (Y. Chen et al., 2023; Fang et al., 2023; Meng & Zhao, 2022; C. Wang & Wang, 2023). This coefficient is applied to annual sectoral value-added data to extract the Three New component, which is then deflated to real terms using sector specific producer price indices with 2016 as the base year.

Sample and Study Period

The study covers 19 administrative units of Taiwan, including 6 special municipalities, 3 cities, and 10 counties. Three outlying island jurisdictions (Penghu, Kinmen, and Lienchiang) are excluded due to limited comprehensive sectoral data. We organize the 19 units into four regional groups. The Northern region includes Taipei, New Taipei, Keelung, Taoyuan, Hsinchu City, Hsinchu County, and Yilan. The Central region includes Miaoli, Taichung, Changhua, Nantou, and Yunlin. The Southern region includes Chiayi City, Chiayi County, Tainan, Kaohsiung, and Pingtung. The Eastern region includes Hualien and Taitung. The study period runs from 2016 to 2022. Primary data sources include DGBAS, NSTC, TIPO, and Taiwan's regional input output tables.

Methods for Analyzing Regional Disparity

Dagum Gini Coefficient

To decompose regional disparities in NQPF, we use the Dagum Gini coefficient (Chang et al., 2023; Hu & Guo, 2022; Lee & Lee, 2022). This method decomposes total disparity into three clearly interpretable components (Pan et al., 2022):

$$\mathrm{G} = \mathrm{Gw} \times \mathrm{Gnb} + \mathrm{Gt} \tag{6}$$

Gw is the contribution from within-region disparity, Gnb is the contribution from between-region disparity, and GtG_t Gt is the contribution from transvariance (sometimes called supervariance), which captures the cross distribution interaction between two different regions. This decomposition gives a more complete picture of spatial heterogeneity than a standard Gini coefficient alone (Liu and Sun, 2023).

Spatial Conditional Kernel Density Estimation

To analyze polarization effects in NQPF, we use spatial conditional kernel density estimation (Luo et al., 2023):

$$f(xIy) = \frac{f(x, y)}{f(y)} \text{ x } \frac{k_h(x_t - x).k_g(y_t - y)}{\int k_h(x_t - x).k_g(y_t - y)dx} \quad (7)$$

In this formula, Kh(·) is a Gaussian kernel function with bandwidth *h* selected by the Silverman rule, x_t is the NQPF of an administrative unit at period *t*, and y_t is the average NQPF of its spatial neighbors at period *t* based on a Queen contiguity spatial weight matrix. This estimator reveals the conditional distribution of NQPF at period *t+1* given the spatial environment at period *t*, allowing us to detect whether neighboring conditions push or pull a region's NQPF forward (X. Zhao et al., 2022).

Spatial Markov Chain

Backwash effects (where advanced regions drain resources from weaker neighbors) and **spread effects** (where advanced regions share knowledge and growth with neighbors) are analyzed using the **spatial Markov chain** method, which extends the conventional Markov chain by incorporating spatial context (P. Zhao et al., 2022) (Le Gallo, 2004). Administrative units are classified into four tiers: Low (L), Medium Low (ML), Medium High (MH), and High (H). The spatial transition probability matrix T_{ijk} represents the probability of transitioning from tier *i* to tier *j* given that the neighboring region belongs to tier *k*. This approach reveals the direction and magnitude of spatial context effects on NQPF mobility between tiers (Zilibotti, 2017).

RESULTS AND DISCUSSION

Overall NQPF Growth in Taiwan

Table 1 summarizes the estimated NQPF growth results for all 19 administrative units from 2016 to 2022. The national average NQPF index is 1.02, with an average annual growth rate of approximately 1.24 percent. Of the 19 units, 12 recorded an index above 1.00, meaning the majority of Taiwan's regions are on a positive growth trajectory, though maintaining sustained momentum remains a structural challenge in several areas.

Table 1. Estimated NQPF Growth by Administrative Unit in Taiwan

Region	Unit	Average	Rank	2016	2017	2018	2019	2020	2021	2022
Northern	Taipei	1.06	4	1.05	1.06	1.06	1.06	1.06	1.07	1.07
	New Taipei	1.04	6	1.03	1.04	1.04	1.04	1.04	1.05	1.04
	Keelung	0.98	15	0.99	0.98	0.98	0.98	0.97	0.97	0.98
	Taoyuan	1.07	3	1.06	1.07	1.07	1.07	1.08	1.08	1.07
	Hsinchu City	1.13	1	1.10	1.12	1.13	1.13	1.14	1.15	1.14
	Hsinchu County	1.11	2	1.08	1.10	1.11	1.11	1.12	1.13	1.12
	Yilan	0.97	16	0.98	0.97	0.97	0.97	0.97	0.96	0.96
Central	Miaoli	1.00	11	1.00	1.00	1.00	1.00	1.00	1.01	1.00
	Taichung	1.05	5	1.04	1.05	1.05	1.05	1.05	1.06	1.05
	Changhua	1.02	9	1.01	1.02	1.02	1.02	1.02	1.02	1.01
	Nantou	0.97	17	0.98	0.97	0.97	0.97	0.96	0.96	0.96
	Yunlin	0.98	14	0.99	0.98	0.98	0.98	0.97	0.98	0.98
Southern	Chiayi City	1.01	10	1.01	1.01	1.01	1.01	1.00	1.01	1.01
	Chiayi County	0.97	18	0.98	0.97	0.97	0.97	0.96	0.96	0.96
	Tainan	1.09	3*	1.06	1.08	1.09	1.09	1.10	1.12	1.11
	Kaohsiung	1.05	7	1.03	1.04	1.05	1.05	1.06	1.06	1.06
	Pingtung	0.96	19	0.97	0.96	0.96	0.96	0.95	0.95	0.96
Eastern	Hualien	0.94	20*	0.95	0.94	0.94	0.93	0.93	0.93	0.93
	Taitung	0.93	21*	0.94	0.93	0.93	0.92	0.92	0.92	0.91
National		1.02		1.02	1.02	1.02	1.02	1.02	1.03	1.02

At the regional level, a clear "North high, East low" pattern is evident. The Northern region's average NQPF (1.051) is well above the Central region (1.004), the Southern region (1.016), and the Eastern region

(0.935). Hsinchu City recorded the highest growth at an average of 1.13, driven by the concentration of its semiconductor ecosystem in the Hsinchu Science Park, home to TSMC, UMC, MediaTek, and hundreds of specialized suppliers. Tainan achieved strong growth at 1.09 as TSMC's mega fabrication facilities expanded into the Southern Taiwan Science Park. At the other end, Hualien and Taitung recorded the lowest values of 0.94 and 0.93 respectively, reflecting the structural constraints of economies dependent on agriculture and tourism with limited Three New Economy capacity. Figure 1 below shows the distribution of NQPF scores across all 19 administrative units.

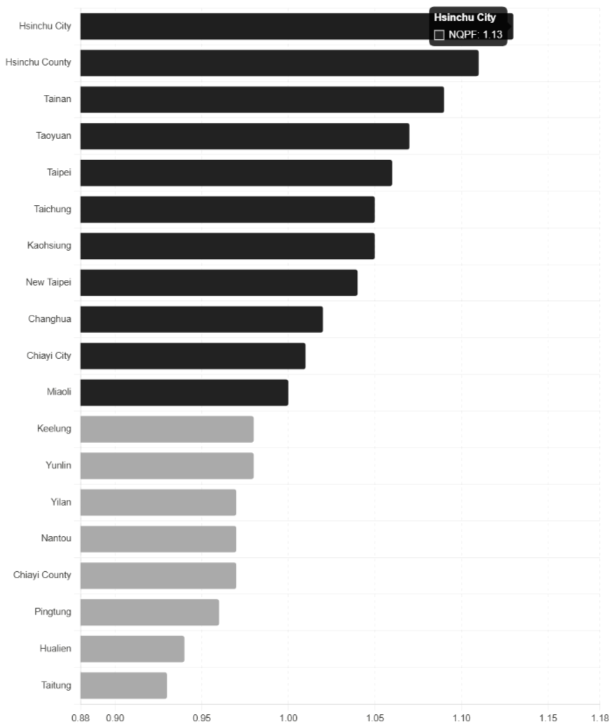

Figure 1. NQPF index by administrative unit in Taiwan

Identifying Six Growth Patterns

By decomposing the Malmquist index into Technical Change (TC) and Efficiency Change (EC), we identify six distinct growth patterns across Taiwan's 19 administrative units. Understanding these patterns is essential because different combinations of TC and EC require different policy responses.

Table 2. Classification of NQPF Growth Patterns in Taiwan

Pattern Name Characteristic	Units	TFP	TC	EC	Key Interpretation
Synchronous Growth	Taipei	1.06	1.07	1.01	Both TC and EC exceed 1.00. Technology innovation and production efficiency improve at the same time. This is the ideal and most balanced growth pattern.
	New Taipei	1.04	1.05	1.01	
	Taoyuan	1.07	1.08	1.01	
	Tainan	1.09	1.10	1.01	
Technology Driven	Hsinchu City	1.13	1.15	0.98	TC is very high but EC is slightly below 1.00. Frontier innovation moves faster than resource allocation can adapt. An efficiency gap exists and needs to be closed.
	Hsinchu County	1.11	1.13	0.98	
Potential Breakthrough	Taichung	1.05	1.06	0.99	TC exceeds 1.00 but EC does not yet follow. Technology is actively advancing but efficiency gains are still catching up with it.
	Miaoli	1.00	1.02	0.98	

Absorption Integration	Kaohsiung	1.05	0.99	1.06	EC exceeds 1.00 but TC does not. Growth relies on absorbing and efficiently using technology transferred from other regions rather than creating new technology locally.
	Changhua	1.02	0.99	1.03	
	Chiayi City	1.01	0.98	1.03	
Incubation	Keelung	0.98	0.97	0.98	Both TC and EC are below 1.00. Innovation capacity and production efficiency are both weak. Strong and sustained external support is required to activate NQPF potential in these regions.
	Yilan	0.97	0.96	0.97	
	Nantou	0.97	0.96	0.97	
	Chiayi County	0.97	0.95	0.96	
	Pingtung	0.96	0.94	0.97	
	Hualien	0.94	0.93	0.96	
	Taitung	0.93	0.92	0.96	
Imitation Catchup	Yunlin	0.98	0.97	1.01	EC is near 1.00, showing genuine effort to absorb external technology. However, limited internal innovation capacity keeps TC below 1.00, so overall TFP remains negative.

Pattern 1, Synchronous Growth, covers Taipei, New Taipei, Taoyuan, and Tainan. All four have both TC and EC above 1.00, which means they are simultaneously advancing their technology frontier and using resources more efficiently. The mature industrial ecosystems in these regions, particularly the semiconductor value chain around the Taoyuan–Taipei corridor and the TSMC mega cluster in Tainan, provide the foundation for this balanced and self-reinforcing growth.

Pattern 2, Technology Driven, applies to Hsinchu City and Hsinchu County. Both have exceptionally high TC values (above 1.13) but slightly negative EC. This tells us that frontier innovation in these regions is moving faster than institutional absorptive capacity and skilled labor allocation can keep up with. Bridging this efficiency gap requires stronger vocational training ecosystems and better labor mobility policies across clusters.

Pattern 3, Potential Breakthrough, covers Taichung and Miaoli. These regions show active innovation investment (TC above 1.00) but efficiency has not yet followed suit (EC slightly below 1.00). Taichung, as a center for precision machinery and electronics, has strong fundamentals to evolve into a Synchronous Growth region by deepening its smart manufacturing value chain integration.

Pattern 4, Absorption Integration, applies to Kaohsiung, Changhua, and Chiayi City. These regions achieve positive NQPF by absorbing and efficiently deploying technology created elsewhere (EC above 1.00), rather than generating new frontier technologies themselves. Kaohsiung's ongoing transition from heavy industry to high technology manufacturing through the Asia New Bay Area development program is a clear example of this strategy.

Pattern 5, Incubation, covers seven units: Keelung, Yilan, Nantou, Chiayi County, Pingtung, Hualien, and Taitung. All have both TC and EC below 1.00. These regions, most of which are agriculture and tourism dependent counties, require fundamental structural transformation before they can organically develop NQPF ecosystems. Without targeted external stimulus, they risk remaining trapped at low productivity levels indefinitely.

Pattern 6, Imitation Catchup, applies to Yunlin alone. Its relatively stable EC (1.01) shows a genuine effort to absorb technology, but limited internal innovation capacity (TC at 0.97) prevents it from achieving an overall positive NQPF trajectory.

Regional Disparities in NQPF

Overall Disparity Trends

Figure 2 shows the Dagum Gini coefficient trends for Taiwan's NQPF, broken down by the four regional groups and the national total.

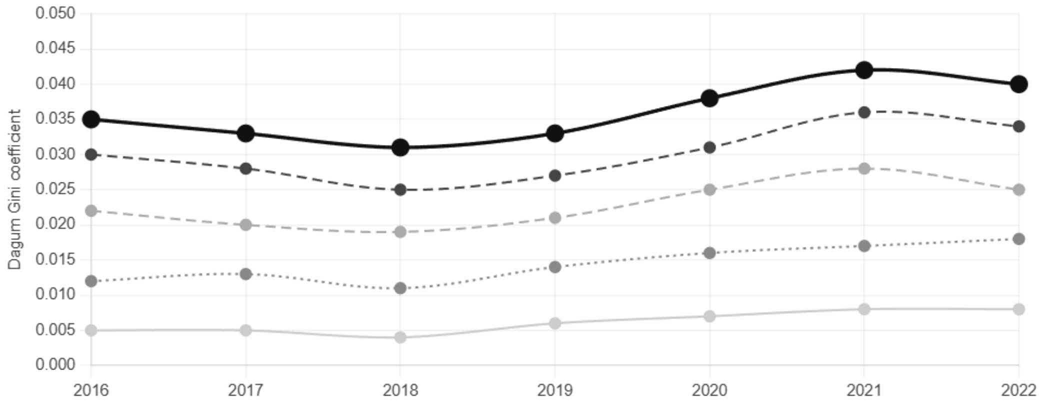

Figure 2. Dagum Gini coefficient trends for NQPF disparity in Taiwan by region

The national total Gini follows a "W" shaped trajectory over the study period. It declined from 0.035 in 2016 to a low of 0.031 in 2018, then reversed sharply upward after 2019, reaching a peak of 0.042 in 2021 before easing slightly to 0.040 in 2022.

The early decline from 2016 to 2018 was driven by the DIGI+ infrastructure program, which distributed digital connectivity investments relatively evenly across Taiwan's regions. The reversal after 2019 is explained by two structural forces. The first is the acceleration of TSMC's investment in Tainan and the expansion of the Hsinchu semiconductor cluster, which dramatically widened the productivity gap with lagging regions. The second is the COVID-19 pandemic, which asymmetrically benefited technology and digital economy regions (the North and Tainan) while hurting tourism and agriculture dependent regions.

Within Region Disparities

Within region Gini values vary considerably across the four groups. The Northern region has the highest within region Gini (average 0.030), reflecting the sharp polarization between the highly productive Hsinchu cluster and the relatively weaker Keelung and Yilan. The Central region shows moderate within region inequality (average 0.014) with an increasing trend at the end of the period, as Taichung pulls further ahead of Nantou and Yunlin. The Southern region experienced the most rapid increase in within region inequality after 2019 (from 0.019 to 0.028), driven by Tainan's explosive growth outpacing the surrounding counties. The Eastern region has the lowest within region Gini (average 0.006), which simply reflects the fact that Hualien and Taitung are both similarly constrained.

Between Region Disparities and Their Sources

Dagum decomposition reveals that between-region disparities account for the largest share of total NQPF inequality, contributing an average of 45.2 percent to the national total Gini. Transvariance (the interaction between distributions across regions) contributes 27.3 percent, and within region disparities contribute 27.5 percent. The dominant role of between region inequality, particularly the North–East and North–Central gaps, confirms that the productivity divide between Taiwan's technology clusters and its peripheral regions is structural and persistent, not a temporary fluctuation.

Coordinated Development Dynamics

Polarization Effects from Kernel Density Analysis

The spatial kernel density analysis reveals a clear bifurcated polarization pattern in Taiwan's NQPF distribution. Over time, low NQPF administrative units tend to remain stuck in a low growth trap, while high NQPF units converge toward even higher levels. The distribution shows multi-peak clustering, indicating the formation of at least two distinct growth poles: the Hsinchu–Taipei–Taoyuan cluster in the North and the Tainan–Kaohsiung corridor in the South.

Spatially, the presence of low NQPF neighbors (particularly in the Eastern region) creates backwash effects that slow down growth in neighboring units such as Yilan and Hualien. This happens because the highly advanced technology clusters drain skilled workers and investment capital away from these adjacent transitional regions. The spatial conditional density shows a shift in weight toward the lower NQPF pole in the conditional distribution, particularly for units surrounded by low performing neighbors.

In the spatiotemporal dimension, NQPF polarization shows a persistent fat tail pattern, especially when a unit's neighboring regions are at the medium high level (index around 1.05 to 1.10). This indicates that medium high regions face a risk of what we call a mid-level trap, where competition between the backwash pull from top clusters and the incomplete spread effects from nearby high performers creates stagnation.

Backwash and Spread Effects: Spatial Markov Chain Analysis

Figure 3 presents the spatial Markov transition probability matrices for Taiwan's NQPF from 2016 to 2022. Administrative units are placed into four tiers: Low (L, TFP below 0.97), Medium Low (ML, TFP from 0.97 to 0.99), Medium High (MH, TFP from 1.00 to 1.05), and High (H, TFP above 1.05). Each of the four panels shows transition probabilities conditional on what tier the spatial neighbors belong to.

Neighbors in Low tier (L)

	L	ML	MH	H
L	**0.56**	0.22	0.14	0.08
ML	0.31	**0.22**	0.27	0.20
MH	0.08	0.08	**0.50**	0.34
H	0.00	0.00	0.18	**0.82**

Neighbors in Medium Low tier (ML)

	L	ML	MH	H
L	**0.82**	0.12	0.06	0.00
ML	0.24	**0.20**	0.44	0.12
MH	0.00	0.25	**0.50**	0.25
H	0.22	0.11	0.23	**0.44**

Neighbors in Medium High tier (MH)

	L	ML	MH	H
L	**0.26**	0.00	0.61	0.13
ML	0.33	**0.42**	0.17	0.08
MH	0.17	0.44	**0.22**	0.17
H	0.20	0.10	0.30	**0.40**

Neighbors in High tier (H)

	L	ML	MH	H
L	**0.84**	0.16	0.00	0.00
ML	0.62	**0.25**	0.13	0.00
MH	0.10	0.20	**0.50**	0.20
H	0.17	0.33	0.33	**0.17**

Figure 3. Spatial Markov transition probability matrices for NQPF in Taiwan

CONCLUSION AND POLICY RECOMMENDATIONS

This study provides a comprehensive analysis of the growth patterns, regional disparities, and coordinated development dynamics of New Quality Productive Forces across 19 administrative units in Taiwan from 2016 to 2022. We combine the super efficiency MinDW Malmquist model, Dagum Gini decomposition, spatial kernel density estimation, and spatial Markov chain analysis to produce a full picture of how NQPF evolves across space and time.

The first conclusion is that Taiwan's NQPF grew moderately at a national average index of 1.02, but this growth is highly concentrated in technology clusters in the Northern region and in the Tainan innovation corridor, while the Eastern region experienced persistent structural stagnation. The second conclusion is that six distinct growth patterns require location specific policy responses rather than a uniform national approach. The third conclusion is that regional NQPF inequality is primarily driven by between-region gaps (contributing 45.2 percent of total Gini), and the divide between the North and the East is structural rather than cyclical. The fourth conclusion is that backwash effects dominate in Low tier regions surrounded by either very weak or very strong neighbors, while spread effects work most efficiently through Medium High relay regions such as Taichung and Kaohsiung.

Recommendation 1: Build a North to South innovation corridor. The government should accelerate integration of the Hsinchu, Taoyuan, and Tainan clusters through physical and digital connectivity infrastructure that facilitates talent mobility and knowledge flows. Creating an innovation corridor linking the Hsinchu Science Park with the Southern Taiwan Science Park would catalyze national NQPF corridor formation.

Recommendation 2: Activate Kaohsiung and Taichung as spread transmitters. Spatial Markov analysis confirms that Medium High regions are the most effective technology spread agents. Strengthening Kaohsiung's capacity in smart manufacturing through the Asia New Bay Area initiative and expanding Taichung's artificial intelligence integration in precision machinery will extend the radius of spread effects into surrounding counties.

Recommendation 3: Apply differentiated transformation strategies for Incubation regions. The seven Incubation pattern units need strategies suited to their specific assets. Regions with natural advantages such as Hualien and Taitung should develop NQPF through green economy platforms, digital eco tourism, and precision agriculture. Regions on the urban to rural boundary such as Yilan and Pingtung should receive stimulus for creative industry development supported by digital connectivity investment.

Recommendation 4: Manage spatial polarization through deliberate investment distribution. Policymakers should consider redistributive incentives that encourage technology spillovers from High to Medium Low regions. These could include technology transfer subsidies, cross regional research residency programs, and the development of satellite technology parks in counties with sufficient absorptive capacity such as Changhua and Miaoli.

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