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A Spatial Econometric Analysis of Fiscal Expenditure and Aging on the Development of the Long-Term Care Industry

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Abstract

Taiwan's elderly population is rising annually and is expected to become a super-aged society by 2025. This study examines the impact of fiscal expenditure and aging on the distribution of long-term care (LTC) facilities across 22 counties and cities from 2000 to 2023 using the Spatial Durbin Model (SDM). Results indicate that economic development and social welfare expenditures boost local LTC facilities but negatively spill over to neighboring areas, while community development and environmental protection expenditures have the opposite effect. The elderly population ratio reduces local LTC facilities but increases them in adjacent areas, whereas the aging index has a positive local effect but a negative spillover. Low- and middle-income elderly allowances support local LTC growth but decrease facilities in neighboring regions. These findings provide insights for optimizing LTC policies and resource allocation.

JEL classification numbers: C21, I18, J14, R12.
Keywords: Aging; Fiscal Expenditure, Spatial Durbin Model, Long-Term Care Facilities, Spatial spillover Effect.

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1. Introduction

The long-term care (LTC) industry is becoming increasingly important globally as the demand for LTC services significantly increases with the aging population (Wang and Tsay 2012). In Taiwan, the elderly population ratio has been rising annually. According to statistics from the Ministry of the Interior, Taiwan entered an aged society in 2020, with the elderly population (65 years and older) accounting for over 15% of the total population. It is expected to become a super-aged society by 2025, with the elderly population ratio reaching over 20%. The Taiwanese government has been facing severe challenges posed by population aging (Chen and Fu 2020). This aging trend brings immense challenges and pressures to the demand for LTC services (Wang et al. 2023). A study on LTC in China shows that most elderly people prefer aging at home, regardless of their health conditions and social support (Ma et al. 2023). However, due to various factors, it is not feasible for all elderly people to age at home. Therefore, the development of the LTC industry has become a crucial part of the social welfare system. Understanding the spatial spillover effects of fiscal expenditure and aging on the development of the LTC industry is essential for formulating effective policies to promote balanced development of the LTC industry.

The number and location of LTC facilities exhibit certain spatial patterns influenced by various factors, including local characteristics and neighborhood effects. However, traditional econometrics assume independence among study subjects, which is inconsistent with reality. LeSage and Pace (2009) pointed out that traditional econometric models ignore spatial effects, often using Ordinary Least Squares (OLS) for model estimation, leading to model specification errors and insufficient explanatory power. Traditional models have limitations in analyzing spatial relationships and numerical correlations, making it difficult to accurately reflect the distribution and changes in the number of LTC facilities across counties and cities.

This study employs spatial econometric methods to explore the factors influencing the development of the LTC industry across counties and cities. A review of previous literature shows relatively few studies have investigated the influencing factors of LTC industry development from the perspective of spatial effects. This paper mainly analyzes the impact of fiscal expenditure and aging on the LTC industry from the perspective of spatial effects, providing a more comprehensive insight.

First, regarding fiscal expenditure, previous studies have demonstrated a significant relationship between government fiscal expenditure and the development of the LTC industry (Jin et al. 2020). Understanding how local government economic development expenditure, social welfare expenditure, community development, and environmental protection expenditure affect the LTC industry is particularly important for counties and cities with scarce LTC resources in Taiwan. Second, regarding the degree of aging, research shows that different regions have varying degrees of aging, impacting the LTC industry differently (Wang et al. 2023).

Understanding the impact of the elderly population ratio, aging index, and the number of approved low- and middle-income elderly living allowances on the development of the LTC industry helps formulate more targeted policies for different regions.

This study contributes by applying spatial econometric methods to the research on the development of the LTC industry, filling a gap in the literature that rarely explores this issue from the perspective of spatial effects. By analyzing the impact of fiscal expenditure and aging on the LTC industry, this study not only identifies the main factors affecting the development of the LTC industry but also highlights their spatial interactions and spillover effects. These findings are valuable for local governments in formulating more effective LTC policies, allocating resources rationally, and promoting balanced development of the LTC industry across regions.

The next section will discuss the relevant literature and hypothesis development regarding the spatial econometric model in LTC industry research, followed by an introduction to the research methodology, including data and sample, research variables, and empirical models. The empirical analysis section will include descriptive statistics and correlation analysis results, spatial autocorrelation test results, and the analysis results of the spatial Durbin model, with an examination of direct and spatial spillover effects. Finally, the study will present conclusions and policy implications.

2. Research Hypotheses

2.1 Fiscal expenditure and the number of long-term care facilities

Fiscal expenditure is an essential tool used by governments to promote economic and social development through various policies (Gu 2023; Nkoro and Otto 2023). Policymakers should take proactive measures. When family care for the elderly is insufficient, the government should intervene and provide enhanced support by implementing appropriate policies and long-term care services to fill this gap (Feng 2019). Specifically, in the long-term care (LTC) industry, fiscal expenditure can directly influence the number and distribution of LTC facilities.

For instance, economic development expenditure typically includes infrastructure construction and industrial support. Economic development expenditure can improve the local economic environment, attract more investments, and thus promote the establishment and operation of LTC facilities. Jin et al. (2020) demonstrated a significant positive relationship between government economic investment and the development of LTC services.

Social welfare expenditure is directly used to improve residents' quality of life, including healthcare and elderly care services. An increase in social welfare expenditure can improve the living conditions of the elderly, increasing the demand for LTC services and thereby promoting an increase in the number of LTC facilities. Fernandez and Forder (2015) pointed out that social welfare expenditure is an important factor affecting the development of LTC services.

Community development expenditure includes community infrastructure construction and public service facilities. Such expenditure can improve the local living environment, increase residents' happiness, and attract more LTC facilities to be established. Renner (2020) showed that improvements in community environments are significantly related to the growth in demand for LTC services.

Environmental protection expenditure is used to improve the local ecological environment and public health. Better environmental conditions can enhance residents' health, reduce disease incidence, and thereby increase the demand for LTC services. A good environment positively impacts the establishment and operation of LTC facilities. Peng et al. (2023) also emphasized the impact of social resource allocation on elderly care resources.

In summary, local fiscal expenditure can significantly influence the number of LTC facilities by improving the economic environment, enhancing social welfare, promoting community development, and protecting the environment. Therefore, this study proposes the following hypothesis regarding the direct effect:

Hypothesis 1a: Local fiscal expenditure has a significant impact on the number of LTC facilities in the local county or city.

2.2 Neighboring counties' fiscal expenditure and its impact

Fiscal expenditure in neighboring counties may influence the number of LTC facilities in a local county through various mechanisms, termed "spatial spillover effects." When neighboring counties increase their fiscal expenditure, particularly in economic development, social welfare, and community development, it may attract or promote the increase in the number of LTC facilities in the local area. For example, if a county has high social welfare expenditure, it may enhance the quality of LTC services and resource allocation, creating a spillover effect on the development of LTC facilities in neighboring counties.

This spillover effect is crucial because the demand and supply of LTC services are not confined to a single county but can be influenced by the policies and resource allocation in surrounding areas. Understanding how neighboring counties' fiscal expenditure affects the local number of LTC facilities is important for formulating coordinated LTC policies and resource allocation strategies across regions. Therefore, this study proposes the following hypothesis regarding the spatial spillover effect:

Hypothesis 1b: Neighboring counties' fiscal expenditure has a significant impact on the number of LTC facilities in the local county or city.

2.3 Aging population and the number of long-term care facilities

As the proportion of the elderly population increases globally, the demand for LTC services also rises continuously (Mori et al. 2020; Polivka and Polivka-West 2020). In Taiwan, the elderly population ratio has been increasing annually, and the aging phenomenon is becoming more pronounced (Chen and Fu 2020). Taiwan's regions still lack comprehensive attention to the LTC needs and experiences of the elderly (Hong 2024). The degree of aging can affect the number of LTC facilities through several aspects.

For example, as the elderly population ratio increases, the demand for LTC services will correspondingly increase. Wang et al. (2023) pointed out in their study that different regions' elderly population ratios have a significant impact on the demand for LTC services. Counties with a higher elderly population ratio will have a higher demand for LTC facilities, thus promoting an increase in the number of these facilities.

The aging index, which measures the ratio of elderly to young populations in a region, also plays a role. A higher aging index indicates greater pressure from the elderly population and a stronger demand for LTC services. Hsiao and Huang (2012) found a significant relationship between the aging index and the development of LTC facilities in Taiwan.

The number of approved low- and middle-income elderly living allowances reflects the living security of local low- and middle-income elderly people. Higher figures indicate more low- and middle-income elderly people needing government-provided LTC services, potentially leading to the establishment of more LTC facilities.

Furthermore, the education and income levels of the elderly population within a region can also influence the demand for LTC facilities. Educated elderly are more likely to understand and utilize LTC services. Mauldin et al. (2020) found that socioeconomic status and racial differences significantly impact LTC facilities.

Different counties' policy measures in response to aging can also affect the number of LTC facilities. Active policy promotion and increased fiscal investment by local governments will enhance LTC services' accessibility and quality. Wu et al. (2009) pointed out that LTC arrangements in rural China are significantly influenced by policy and economic conditions. Therefore, this study proposes the following hypothesis regarding the direct effect of aging:

Hypothesis 2a: The degree of aging in a local county or city has a significant impact on the number of LTC facilities in that county or city.

2.4 Neighboring counties' aging degree and its impact

The aging degree in neighboring counties may significantly influence the number of LTC facilities in a local county through various mechanisms, termed "spatial spillover effects." For instance, regarding demand spillover effects, when a county has a high aging degree, its demand for LTC services will increase. If the county's LTC resources are insufficient, the elderly might seek LTC services in neighboring areas, increasing the demand for LTC facilities in those areas.

Policy imitation effects may also emerge, whereby neighboring counties emulate the long-term care (LTC) policies and strategies implemented in regions with higher levels of population aging. When a county adopts effective LTC measures to address the challenges of an aging society, surrounding counties may replicate or adopt similar approaches. This policy diffusion can further stimulate the establishment and operation of LTC facilities across neighboring regions, thereby amplifying the impact of successful local policy interventions.

Costa-Font and Moscone (2008) noted interdependence in public health expenditure among neighboring regions, which might also exist in LTC service demand. When a region is rich in LTC resources, neighboring regions' demand may increase.

Regional cooperation in resource sharing to address aging challenges may involve jointly establishing and operating LTC facilities, improving accessibility and quality. This cooperation can increase the number of LTC facilities in neighboring counties.

Moreover, in modern society, the elderly may migrate to neighboring areas for various reasons (e.g., proximity to relatives or better living environments), leading to increased elderly populations in those areas and higher demand for LTC services, prompting more LTC facilities to be established.

These phenomena suggest that the aging degree in neighboring counties significantly affects the number of LTC facilities in a local county, involving cross-regional interactions and dependencies. Therefore, this study proposes the following hypothesis regarding the spatial spillover effect:

Hypothesis 2b: The degree of aging in neighboring counties has a significant impact on the number of LTC facilities in the local county or city.

3. Methodology

3.1 Data and sample

This study uses panel data from 22 counties and cities in Taiwan, covering the years 2000 to 2023. Taiwan currently has 6 municipalities, 13 counties, and 3 cities, which constitute the highest level of local government entities. The data were sourced from the County and City Major Statistical Indicators Query System on the statistical information website released by the Directorate General of Budget, Accounting and Statistics (DGBAS) of the Executive Yuan in 2024.

As shown in Table 1, the number of elderly long-term care and nursing facilities in Taiwan increased from 507 in 2000 to 1,042 in 2009. There was a slight decrease in the number of facilities between 2010 and 2013, reaching 1,012 in 2013. The number of facilities began to increase again in 2014, reaching 1,059 in 2016, surpassing the 1,000 mark, and peaking at 1,076 in 2017. However, following the outbreak of the COVID-19 pandemic in 2020, the number of facilities decreased, dropping to 1,032 in 2023.

Table 1: Number of elderly long-term care and nursing facilities in Taiwan from 2000 to 2023

Year	Number of Facilities	Year	Number of Facilities	Year	Number of Facilities
2000	507	2008	1018	2016	1,059
2001	634	2009	1042	2017	1,076
2002	757	2010	1029	2018	1,075
2003	803	2011	1028	2019	1,068
2004	862	2012	1012	2020	1,055
2005	888	2013	1012	2021	1,056
2006	920	2014	1040	2022	1,042
2007	978	2015	1044	2023	1,032

Source: The Directorate General of Budget, Accounting and Statistics (DGBAS) of the Executive Yuan (2024).

3.2 Research variables

In the empirical model constructed for this study, the definitions and descriptions of the dependent and independent variables are as follows.

3.2.1 Dependent variable

Number of long-term care and nursing homes ($NLCNH_{it}$): This refers to the number of public and private long-term care and nursing homes in the i-th county or city of Taiwan in year t. The number includes:

Long-term care institutions:

1. Long-term care type: Institutions that care for elderly individuals with chronic diseases requiring medical services.
2. Nursing type: Institutions that care for elderly individuals with disabilities needing assistance or those requiring services like nasogastric tubes, gastrostomy, and catheterization.
3. Dementia care type: Institutions that care for elderly individuals diagnosed with moderate or severe dementia by specialists and who need care.
4. Nursing homes: Institutions that care for elderly individuals who need assistance or have no relatives obligated to support them, or whose relatives lack the ability to support them, but can manage daily life activities.

3.2.2 Independent variables

Fiscal expenditure variables include economic development expenditure, social welfare expenditure, and community development and environmental protection expenditure.

1. Economic development expenditure (EDE_{it}) (in million NTD): This refers to the economic development expenditure of the i-th county or city of Taiwan in year t. It includes expenditures related to agriculture, industry, transportation,

and other economic services handled by the county or city.

2. Social welfare expenditure (SWE_{it}) (in million NTD): This refers to the social welfare expenditure of the i-th county or city of Taiwan in year t. It includes expenditures related to social insurance, social assistance, welfare services, national employment, healthcare, and subsidies managed by the county or city.
3. Community development and environmental protection expenditure (CEE_{it}) (in million NTD): This refers to the community development and environmental protection expenditure of the i-th county or city of Taiwan in year t. It includes expenditures related to community development, environmental protection, and subsidies managed by the county or city.

Aging variables include the number of businesses, average disposable income per household, and others.

1. Proportion of elderly population (65 and above) (PEP_{it}) (%): This refers to the proportion of the population aged 65 and above in the i-th county or city of Taiwan in year t. The calculation formula is: (Number of people aged 65 and above ÷ Total registered population) × 100.
2. Aging index (AGI_{it}) (%): This refers to the aging index of the i-th county or city of Taiwan in year t. The aging index measures the degree of population aging in a region, calculated as: (Number of people aged 65 and above ÷ Number of people aged 14 and below) × 100.
3. Number of approved low- and middle-income elderly living allowances $(NLMA_{it})$ (persons): This refers to the number of approved low- and middle-income elderly living allowances in the i-th county or city of Taiwan in year t. It refers to the number of approvals issued by the competent authorities of the municipality or county (city) where the household is registered, in accordance with the Social Assistance Act and the Regulations for the Issuance of Living Allowances for Low- and Middle-Income Elderly.

3.3 Empirical model

This study examines the spatial effects on the development of the long-term care (LTC) industry in various counties and cities in Taiwan from the perspective of spatial econometrics, using a spatial panel data model. Given the differing fiscal conditions and degrees of aging across Taiwan's counties and cities, the empirical model constructed for this study is as follows:

$$
\begin{aligned}
NLCNH_{it} = {} & \rho \sum_{j=1}^{N} W_{ij} NLCNH_{jt} + \alpha + \beta_1 EDE_{it} + \beta_2 SWE_{it} + \beta_3 CEE_{it} \\
& + \beta_4 PEP_{it} + \beta_5 AGI_{it} + \beta_6 NLMA_{it} + \theta_1 \sum_{j=1}^{N} W_{ij} EDE_{jt} \\
& + \theta_2 \sum_{j=1}^{N} W_{ij} SWE_{jt} + \theta_3 \sum_{j=1}^{N} W_{ij} CEE_{jt} + \theta_4 \sum_{j=1}^{N} W_{ij} PEP_{jt} \\
& + \theta_5 \sum_{j=1}^{N} W_{ij} AGI_{jt} + \theta_6 \sum_{j=1}^{N} W_{ij} NLMA_{jt} + \mu_i + \varepsilon_{it} \\
& \qquad \mathrm{i} \neq \mathrm{j}
\end{aligned}
$$

Where:
$NLCNH_{it}$ is the dependent variable (number of long-term care and nursing homes) in county or city i in year t.
i, j are counties or cities in Taiwan.
t represents the year (2000-2023).

W_{ij} is the spatial weight matrix, a symmetric matrix with dimensions equal to the number of counties and cities (22 in this study). This study uses queen contiguity to define spatial adjacency, where counties sharing an edge or corner are considered neighbors (Sawada 2004). The contiguity matrix defines the adjacency relationship, with values of 1 for neighboring counties and cities, and 0 otherwise (including the diagonal). For Taiwan's three island counties with no neighbors, the values are set to 0. The spatial weight matrix is defined as:

$$
W_{ij} = \begin{cases} 1, & regions\ i\ and\ j\ are\ neighboring\ regions \\ 0, & regions\ i\ and\ j\ are\ not\ neighboring\ regions \end{cases}
$$

ρ is the spatial lag coefficient, reflecting the spatial autocorrelation of the dependent variable. It indicates the direction and magnitude of the impact of the dependent variable $NLCNH_{jt}$ in neighboring regions j on the dependent variable $NLCNH_{it}$ in region i. By testing the spatial lag coefficient ρ, the spillover effects of neighboring regions on the local region can be further explored. A significant ρ indicates a clear spatial dependence among the dependent variables. If $\rho \neq 0$, it indicates a spatial relationship between neighboring regions. A positive ρ (ρ>0) indicates the presence of positive spatial spillover effects. The magnitude of ρ reflects the degree of spatial diffusion or spatial spillover interactions among regions.
$W_{ij}NLCNH_{jt}$ is the spatial autocorrelation matrix of the dependent variable, an endogenous variable showing the impact of $NLCNH_{jt}$ in neighboring region j on $NLCNH_{it}$ in region i.

α is the constant term. β represents the coefficients to be estimated, indicating the original effect coefficients.

EDE_{it} (economic development expenditure), SWE_{it} (social welfare expenditure), CEE_{it} (community development and environmental protection expenditure), PEP_{it} (proportion of elderly population (65 and above)), AGI_{it} (aging index), $NLMA_{it}$ (number of approved low- and middle-income elderly living allowances) are the independent variables.

$\beta_1 EDE_{it}$, $\beta_2 SWE_{it}$, $\beta_3 CEE_{it}$, $\beta_4 PEP_{it}$, $\beta_5 AGI_{it}$, $\beta_6 NLMA_{it}$ reflect the impact of each independent variable on $NLCNH_{it}$.

θ represents the coefficients to be estimated for the spatial autocorrelation terms of the independent variables. These coefficients reflect the impact of all independent variables in neighboring regions on $NLCNH_{it}$ in region i. A positive θ indicates that the neighboring regions' effects positively influence the dependent variable $NLCNH_{it}$, suggesting the presence of spillover effects. A negative θ indicates competitive effects among neighboring regions.

$W_{ij}EDE_{jt}$, $W_{ij}SWE_{jt}$, $W_{ij}CEE_{jt}$, $W_{ij}PEP_{jt}$, $W_{ij}AGI_{jt}$, $W_{ij}NLMA_{jt}$ are the spatial autocorrelation matrices of the independent variables, indicating the spatial effects of all independent variables, showing the impact of the independent variables in neighboring regions on $NLCNH_{it}$ in region i.

μ_i represents the spatial (individual) effects, the individual effects of county or city i.

ε_{it} is the independently and identically distributed random error term, representing spatially autocorrelated error terms.

4. Results

4.1 Descriptive statistics and correlation analysis

Tables 2 and 3 respectively present the descriptive statistics and correlation analysis results for the variables in the model of this study. Table 2 summarizes the descriptive statistics of the variables used in this study. These variables include the number of long-term care and nursing homes (NLCNH), economic development expenditure (EDE), social welfare expenditure (SWE), community development and environmental protection expenditure (CEE), proportion of elderly population (65 and above) (PEP), aging index (AGI), and the number of approved low- and middle-income elderly living allowances (NLMA). The specific data are as follows: Number of long-term care and nursing homes (NLCNH): The mean value is 43.63, with a minimum of 0 and a maximum of 219.00. Economic development expenditure (EDE): The mean value is 7290.35 million NTD, with a minimum of 541.91 and a maximum of 46357.08. Social welfare expenditure (SWE): The mean value is 6368.62 million NTD, with a minimum of 180.82 and a maximum of 44720.84. Community development and environmental protection expenditure (CEE): The mean value is 2421.69 million NTD, with a minimum of 63.44 and a maximum of 20164.01. Proportion of elderly population (65 and above) (%) (PEP): The mean value is 12.96%, with a minimum of 6.37% and a maximum of 22.36%.

Aging index (AGI) (%): The mean value is 93.07, with a minimum of 29.48 and a maximum of 263.11. Number of approved low- and middle-income elderly living allowances (NLMA) (persons): The mean value is 6867.30, with a minimum of 4 and a maximum of 44136.

Table 3 shows the Pearson correlation coefficients between the main variables. Key findings include:

The correlation coefficient between the number of long-term care and nursing homes (NLCNH) and economic development expenditure (EDE) is 0.795. The correlation coefficient between NLCNH and social welfare expenditure (SWE) is 0.800. The correlation coefficient between NLCNH and community development and environmental protection expenditure (CEE) is 0.841. All these correlation coefficients are significant at the 0.01 level. The correlation coefficient between the aging index (AGI) and the proportion of elderly population (65 and above) (PEP) is 0.936, showing a strong positive correlation, significant at the 0.01 level. The correlation coefficients between the number of approved low- and middle-income elderly living allowances (NLMA) and various variables (such as economic development expenditure, social welfare expenditure, and community development and environmental protection expenditure) are also significant at the 0.01 level.

These descriptive statistics and correlation analysis results lay the foundation for the subsequent spatial econometric model analysis, helping us understand the basic relationships and interactions between the variables.

Table 2: Summary of descriptive statistics

Variables	Obs.	Mean	Std. Dev.	Min.	25th Percentile	Median	75th Percentile	Max.
NLCNH	528	43.63	51.68	0.00	11.50	21.50	54.50	219.00
EDE	528	7290.35	7622.95	541.91	2572.15	4207.69	8151.56	46357.08
SWE	528	6368.62	8321.01	180.82	1754.21	2854.05	6055.50	44720.84
CEE	528	2421.69	3805.22	63.44	324.42	690.35	1884.85	20164.01
PEP	528	12.96	3.25	6.37	10.59	12.65	15.01	22.36
AGI	528	93.07	43.58	29.48	59.74	82.43	118.82	263.11
NLMA	528	6867.30	7558.61	4.00	1788.50	5244.50	8950.50	44136.00

Note: Obs.: Observations.
NLCNH: Number of Long-term Care and Nursing Homes, EDE: Economic Development Expenditure (in million NTD), SWE: Social Welfare Expenditure (in million NTD), CEE: Community Development and Environmental Protection Expenditure (in million NTD), PEP: Proportion of Elderly Population (65 and above) (%), AGI: Aging Index (%), Number of Approved Low- and Middle-Income Elderly Living Allowances (persons).
NTD: New Taiwan dollar (equal to USD 0.030).

Table 3: Pearson correlation analysis

	NLCNH	EDE	SWE	CEE	PEP	AGI	NLMA
NLCNH	1						
EDE	.795**	1					
SWE	.800**	.866**	1				
CEE	.841**	.877**	.917**	1			
PEP	-.084	.030	.105*	-.055	1		
AGI	-.023	.055	.108*	-.023	.936**	1	
NLMA	.716**	.715**	.723**	.700**	-.044	-.024	1

Note: * $p<0.05$; ** $p<0.01$.
NLCNH: Number of Long-term Care and Nursing Homes, EDE: Economic Development Expenditure (in million NTD), SWE: Social Welfare Expenditure (in million NTD), CEE: Community Development and Environmental Protection Expenditure (in million NTD), PEP: Proportion of Elderly Population (65 and above) (%), AGI: Aging Index (%), Number of Approved Low- and Middle-Income Elderly Living Allowances (persons).
NTD: New Taiwan dollar (equal to USD 0.030).

4.2 Spatial autocorrelation test results

The range of Moran's I index values is [-1, 1]. Values closer to 1 indicate a stronger positive spatial autocorrelation, while values closer to -1 indicate a stronger negative spatial autocorrelation (Moran 1950). In this study, we use Moran's I index to detect spatial autocorrelation to determine the spatial distribution correlation of the number of long-term care and nursing homes.

From Table 4, our analysis covers data from 2000 to 2023. The results show that the Moran's I index values are positive for all years, and the p-values for most years are less than 0.05, indicating significant positive spatial autocorrelation. This means that in Taiwan, the number of long-term care and nursing homes in each county or city is significantly clustered spatially, where the number of facilities in a particular county or city tends to be positively correlated with the number in neighboring counties or cities.

In 2000, the Moran's I index was 0.266, with a p-value of 0.003, indicating significant positive spatial autocorrelation for that year. In 2012, the Moran's I index reached 0.357, with a p-value of 0.014, again showing significant positive spatial autocorrelation. In 2004 and 2005, the Moran's I indices were 0.506 and 0.519, respectively, the highest among all years, indicating the strongest spatial clustering of long-term care and nursing homes in Taiwan during these two years, with highly significant p-values ($p < 0.001$).

Furthermore, the overall trend from 2000 to 2023 shows that the Moran's I index exceeds 0.3 for most years, with p-values less than 0.05, indicating a consistent and stable spatial autocorrelation in the number of long-term care and nursing homes in Taiwan during this period.

These results indicate significant spatial autocorrelation in the distribution of long-term care and nursing homes across Taiwan's counties and cities, showing that these facilities are not randomly distributed but are significantly clustered spatially. These findings have important implications for formulating targeted policy measures and resource allocation.

Table 4: Spatial autocorrelation indicators from 2000 to 2023

Year	Moran's I		Year	Moran's I	
	I	*p*-value		I	*p*-value
2000	0.266	0.003	2012	0.357	0.014
2001	0.435	0.000	2013	0.319	0.024
2002	0.467	0.000	2014	0.313	0.025
2003	0.473	0.000	2015	0.309	0.026
2004	0.506	0.000	2016	0.297	0.032
2005	0.519	0.000	2017	0.275	0.043
2006	0.513	0.001	2018	0.283	0.038
2007	0.476	0.001	2019	0.279	0.041
2008	0.443	0.003	2020	0.273	0.045
2009	0.432	0.004	2021	0.271	0.047
2010	0.420	0.005	2022	0.270	0.047
2011	0.398	0.007	2023	0.262	0.052

4.3 Wald test and likelihood-ratio test results

LeSage and Pace (2009) and Elhorst (2010) suggest that the Spatial Durbin Model (SDM) can be simplified to either the Spatial Lag Model (SLM) or the Spatial Error Model (SEM). The following hypothesis tests are conducted to select the appropriate model. If the null hypothesis H_0: $\theta = 0$ is rejected, SDM cannot be simplified to SLM, making SDM a more reasonable choice. Similarly, if H_0: $\theta + \rho\beta = 0$ is rejected, SDM cannot be simplified to SEM, making SDM a more reasonable choice.

Table 5 shows the comparative analysis results between SLM and SDM, including models with spatial fixed effects, time fixed effects, and both spatial and time fixed effects:

SLM vs. SDM (spatial fixed effects): Wald test shows $x^2 = 534.42$, $p < 0.001$, and Likelihood-ratio test shows $x^2 = 368.22$, $p < 0.001$. The results suggest that SDM with spatial fixed effects is more reasonable.

SLM vs. SDM (time fixed effects): Wald test shows $x^2 = 58.47$, $p < 0.001$, and Likelihood-ratio test shows $x^2 = 83.27$, $p < 0.001$. The results suggest that SDM with time fixed effects is more reasonable.

SLM vs. SDM (spatial and time fixed effects): Wald test shows $x^2 = 174.48$, $p < 0.001$, and Likelihood-ratio test shows $x^2 = 153.42$, $p < 0.001$. The results suggest that SDM with spatial and time fixed effects is more reasonable.

SLM vs. SDM (random effects): Wald test shows $x^2 = 489.32$, $p < 0.001$, and Likelihood-ratio test shows $x^2 = 335.21$, $p < 0.001$. The results suggest that SDM with random effects is more reasonable.

Table 6 shows the comparative analysis results between SEM and SDM, including models with spatial fixed effects, time fixed effects, and both spatial and time fixed effects:
SEM vs. SDM (spatial fixed effects): Wald test shows x^2 = 528.11, p < 0.001, and Likelihood-ratio test shows x^2 = 333.29, p < 0.001. The results suggest that SDM with spatial fixed effects is more reasonable.
SEM vs. SDM (time fixed effects): Wald test shows x^2 = 528.11, p < 0.001, and Likelihood-ratio test shows x^2 = 333.29, p < 0.001. The results suggest that SDM with time fixed effects is more reasonable.
SEM vs. SDM (spatial and time fixed effects): Wald test shows x^2 = 296.75, p < 0.001, and Likelihood-ratio test shows x^2 = 211.40, p < 0.001. The results suggest that SDM with spatial and time fixed effects is more reasonable.
SEM vs. SDM (random effects): Wald test shows x^2 = 464.48, p < 0.001, and Likelihood-ratio test shows x^2 = 288.27, p < 0.001. The results suggest that SDM with random effects is more reasonable.
Based on the above test results, it can be concluded that regardless of spatial fixed effects, time fixed effects, or random effects, the SDM is more reasonable and applicable compared to SLM and SEM.

Table 5: Spatial lag model (SLM)

Variables	Model 1 SLM with spatial fixed-effects		Model 2 SLM with time fixed-effects		Model 3 SLM with spatial and time fixed-effects		Model 4 SLM with random-effects	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDE	0.001***	0.000	0.001*	0.000	0.001***	0.000	0.001***	0.000
SWE	0.001***	0.000	0.000	0.000	0.001***	0.000	0.001***	0.000
CEE	-0.003***	0.001	0.006***	0.001	-0.003***	0.001	-0.002**	0.001
PEP	-1.968*	0.860	-5.094***	0.959	0.110	0.737	-2.811**	0.891
AGI	0.193***	0.054	0.363***	0.080	0.171**	0.052	0.226***	0.056
NLMA	0.001*	0.000	0.002***	0.000	0.002***	0.000	0.001***	0.000
Constant							39.980***	9.591
n		528		528		528		528
Spatial ρ	-0.107	0.060	0.151***	0.036	-0.441***	0.054	-0.020	0.061
within R^2	0.269		0.124		0.324		0.253	
between R^2	0.660		0.861		0.403		0.712	
overall R^2	0.557		0.762		0.374		0.628	
Log-likelihood	-2136.638		-2433.103		-2003.663		-2204.950	
Wald test	$H_0: \theta = 0$ x^2 = 534.42*** p-value = 0.000		$H_0: \theta = 0$ x^2 = 58.47*** p-value = 0.000		$H_0: \theta = 0$ x^2 = 174.48*** p-value = 0.000		$H_0: \theta = 0$ x^2 = 489.32*** p-value = 0.000	
Likelihood-ratio test	H_0: SLM nested within SDM LR x^2 = 368.22*** p-value = 0.000		H_0: SLM nested within SDM LR x^2 = 83.27*** p-value = 0.000		H_0: SLM nested within SDM LR x^2 = 153.42*** p-value = 0.000		H_0: SLM nested within SDM LR x^2 = 335.21*** p-value = 0.000	

Note: * p<0.05; ** p<0.01; *** p<0.001
SLM: Spatial lag model. SDM: Spatial Durbin model. Coef.: Coefficient. Std. Err.: Standard error.
NLCNH: Number of Long-term Care and Nursing Homes, EDE: Economic Development Expenditure (in million NTD), SWE: Social Welfare Expenditure (in million NTD), CEE: Community Development and Environmental Protection Expenditure (in million NTD), PEP: Proportion of Elderly Population (65 and above) (%), AGI: Aging Index (%), Number of Approved Low- and Middle-Income Elderly Living Allowances (persons).
NTD: New Taiwan dollar (equal to USD 0.030).

Table 6: Spatial error model (SEM)

Variables	**Model 5 SEM with spatial fixed-effects**		**Model 6 SEM with time fixed-effects**		**Model 7 SEM with spatial and time fixed-effects**		**Model 8 SEM with random-effects**	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDE	0.001***	0.000	0.001**	0.000	0.001***	0.000	0.001***	0.000
SWE	0.001***	0.000	0.001*	0.000	0.001***	0.000	0.001***	0.000
CEE	-0.002**	0.001	0.006**	0.001	-0.003***	0.001	-0.002*	0.001
PEP	-3.619***	0.817	-5.567	1.013	-0.446	0.757	-3.923***	0.820
AGI	0.231***	0.050	0.479	0.086	0.158**	0.054	0.243***	0.051
NLMA	0.003***	0.000	0.001***	0.000	0.002***	0.000	0.003***	0.000
Constant							36.107***	8.871
n		528		528		528		528
Spatial λ	0.448***	0.051	-0.112	0.064	-0.335***	0.073	0.460***	0.049
within R^2	0.203		0.160		0.210		0.201	
between R^2	0.673		0.853		0.478		0.691	
overall R^2	0.612		0.746		0.417		0.629	
Log-likelihood	-2119.176		-2432.749		-2032.650		-2181.476	
Wald test	H_0: $\theta+\rho\beta=0$ x^2 = 528.11*** p-value = 0.000		H_0: $\theta+\rho\beta=0$ x^2 = 68.71*** p-value = 0.000		H_0: $\theta+\rho\beta=0$ x^2 = 296.75*** p-value = 0.000		H_0: $\theta+\rho\beta=0$ x^2 = 464.48*** p-value = 0.000	
Likelihood-ratio test	H_0: SEM nested within SDM LR x^2 = 333.29*** p-value = 0.000		H_0: SEM nested within SDM LR x^2 = 82.56*** p-value = 0.000		H_0: SEM nested within SDM LR x^2 = 211.40*** p-value = 0.000		H_0: SEM nested within SDM LR x^2 = 288.27*** p-value = 0.000	

Note: * p<0.05; ** p<0.01; *** p<0.001
SEM: Spatial error model. SDM: Spatial Durbin model. Coef.: Coefficient. Std. Err.: Standard error.
NLCNH: Number of Long-term Care and Nursing Homes, EDE: Economic Development Expenditure (in million NTD), SWE: Social Welfare Expenditure (in million NTD), CEE: Community Development and Environmental Protection Expenditure (in million NTD), PEP: Proportion of Elderly Population (65 and above) (%), AGI: Aging Index (%), Number of Approved Low- and Middle-Income Elderly Living Allowances (persons).
NTD: New Taiwan dollar (equal to USD 0.030).

4.4 Hausman test results

This study employs the Hausman test proposed by Hausman (1978) to determine whether the random effects model or the fixed effects model is more appropriate. Table 7 presents the Hausman test results for the SDM.

Hausman Test for SDM with spatial fixed effects vs. SDM with random effects: The Hausman test shows x^2 = 9.83, $p > 0.05$. The null hypothesis (random effects model) cannot be rejected. Therefore, in this case, the random effects model is more suitable than the fixed effects model.

Hausman Test for SDM with time fixed effects vs. SDM with random effects: The Hausman test shows x^2 = 69.86, $p < 0.001$. The null hypothesis (random effects model) is rejected. Therefore, in this case, the fixed effects model is more suitable than the random effects model.

Hausman Test for SDM with spatial and time fixed effects vs. SDM with random effects: The Hausman test shows x^2 = 10.03, $p > 0.05$. The null hypothesis (random effects model) cannot be rejected. Therefore, in this case, the random effects model is more suitable than the fixed effects model.

Based on the above analysis results, this study needs to compare and test between SDM with time fixed effects and SDM with random effects to determine which model is more appropriate. For the SDM models with spatial fixed effects and time fixed effects, the random effects model is more suitable, while for the SDM model with only time fixed effects, the fixed effects model is more suitable. Therefore, the focus of the subsequent analysis in this study should be on comparing SDM with time fixed effects and SDM with random effects to ensure the most appropriate model is chosen for further analysis.

Table 7: Hausman test results

Model Comparison	**Hausman test**		**Result**
	x^2	p-value	
SDM with spatial fixed-effects v.s. SDM with random-effects	9.83	0.1321	H_0: $\mathrm{E}(x_{it}, \mu_i) = 0$ Null hypothesis (random effects model) cannot be rejected. Use SDM with random effects.
SDM with time fixed-effects v.s. SDM with random-effects	69.86	0.0000	H_0: $\mathrm{E}(x_{it}, \mu_i) = 0$ Null hypothesis (random effects model) is rejected. Use SDM with time fixed effects.
SDM with spatial and time fixed-effects v.s. SDM with random-effects	10.03	0.1234	H_0: $\mathrm{E}(x_{it}, \mu_i) = 0$ Null hypothesis (random effects model) cannot be rejected. Use SDM with random effects.

4.5 Spatial Durbin model analysis results

Table 8 presents the estimation results for four types of Spatial Durbin Models (SDM). Since Models 9 and 11 were not considered based on the Hausman test results, this study focuses on comparing and testing between SDM with time fixed effects (Model 10) and SDM with random effects (Model 12).

When evaluating the overall fit of the models, spatial econometric models use Maximum Likelihood Estimation (MLE). The fit indicators include Log Likelihood (LIK), Akaike Information Criterion (AIC), and Schwarz Bayesian Information Criterion (SBC or BIC). The model with the highest Log Likelihood value or the lowest AIC and BIC values is considered the best model.

The comparison results are as follows: Model 12 (SDM with random effects) has better Log Likelihood, AIC, and BIC values than Model 10. The spatial lag coefficient ρ in Model 10 (SDM with time fixed effects) is not significant ($\rho = -0.066$, $p > 0.05$). In contrast, the spatial lag coefficient ρ in Model 12 is significant ($\rho = -0.137$, $p < 0.01$), indicating a significant negative spatial correlation in the distribution of long-term care and nursing homes across counties and cities, which further justifies incorporating spatial effects into the econometric model.

Therefore, this study ultimately decides to use Model 12 (SDM with random effects) as the basis for subsequent analysis. From the above analysis results, it is evident that SDM with random effects (Model 12) performs best in evaluating the distribution of long-term care and nursing homes across Taiwan's counties and cities. Its significant spatial lag coefficient indicates a significant negative spatial correlation in the number of long-term care and nursing homes, which further confirms the importance of spatial effects in studying the distribution of these facilities. The subsequent analysis will be based on Model 12, providing more reliable evidence for policy-making.

Table 8: Spatial Durbin model analysis results

Variables	**Model 9 SDM with spatial fixed-effects**		**Model 10 SDM with time fixed-effects**		**Model 11 SDM with spatial and time fixed-effects**		**Model 12 SDM with random-effects**	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDE	0.001^{***}	0.000	0.000	0.000	0.001^{***}	0.000	0.001^{***}	0.000
SWE	0.001^{***}	0.000	0.001	0.000	0.001^{***}	0.000	0.001^{***}	0.000
CEE	-0.002^{**}	0.001	0.007^{***}	0.001	-0.002^{***}	0.001	-0.002^{**}	0.001
PEP	-3.321^{***}	0.814	-8.823^{***}	1.034	-2.155^{*}	0.864	-3.333^{***}	0.813
AGI	0.133^{**}	0.039	0.652^{***}	0.088	0.152^{**}	0.048	0.142^{***}	0.040
NLMA	0.001^{***}	0.000	0.001^{***}	0.000	0.002^{***}	0.000	0.001^{***}	0.000
W×EDE	-0.001^{***}	0.000	-0.001	0.000	-0.001^{***}	0.000	-0.001^{***}	0.000
W×SWE	-0.001^{***}	0.000	-0.001	0.001	-0.001^{**}	0.000	-0.001^{***}	0.000
W×CEE	0.001	0.001	0.004^{**}	0.001	0.001	0.001	0.001^{*}	0.001
W×PEP	10.617^{***}	1.289	-0.895	0.708	6.617^{***}	1.377	9.892^{***}	1.275
W×AGI	-0.318^{***}	0.064	0.270^{**}	0.083	-0.156^{*}	0.069	-0.292^{***}	0.065
W×NLMA	-0.006^{***}	0.000	0.001^{*}	0.000	-0.004^{***}	0.000	-0.005^{***}	0.000
Constant							26.014	13.450
n		528		528		528		528
Spatial ρ	-0.179^{***}	0.051	-0.066	0.065	-0.314^{***}	0.054	-0.137^{**}	0.053
within R^2	0.613		0.123		0.587		0.615	
between R^2	0.074		0.893		0.117		0.085	
overall R^2	0.102		0.758		0.152		0.115	
Log-likelihood	-1952.529		-2391.470		-1926.951		-2037.344	
AIC	3933.058		4810.940		3881.901		4106.687	
BIC	3992.825		4870.708		3941.669		4174.993	

Note: * $p<0.05$; ** $p<0.01$; *** $p<0.001$
SDM: Spatial Durbin model.
Coef.:Coefficient
Std. Err.: Standard error.
NLCNH: Number of Long-term Care and Nursing Homes, EDE: Economic Development Expenditure (in million NTD), SWE: Social Welfare Expenditure (in million NTD), CEE: Community Development and Environmental Protection Expenditure (in million NTD), PEP: Proportion of Elderly Population (65 and above) (%), AGI: Aging Index (%), Number of Approved Low- and Middle-Income Elderly Living Allowances (persons).
NTD: New Taiwan dollar (equal to USD 0.030).

4.6 Decomposition results of the SDM with random effects

LeSage and Pace (2009) pointed out that in the Spatial Durbin Model (SDM), which accounts for spatial interaction effects, relying solely on the estimated regression coefficients of spatial parameters to determine the existence of spatial spillover effects may lead to biased conclusions due to the presence of feedback effects. Since the SDM includes both spatially lagged independent and dependent variables, the estimated coefficients do not directly reflect marginal effects, making it difficult to accurately assess the true influence of explanatory variables on the dependent variable (Elhorst, 2010). Therefore, the model estimates must be decomposed into direct effects, indirect effects (i.e., spatial spillover effects), and total effects to fully understand the mechanisms of influence. Table 9 presents the decomposition results of the SDM with random effects.

In terms of fiscal expenditures, the analysis shows that economic development expenditure (EDE) has a positive direct effect on the number of LTC facilities within the local county or city, indicating that increasing this expenditure supports the establishment and expansion of local care institutions. However, its indirect effect is negative, suggesting that as one region strengthens its investment in economic development, it may suppress the development of LTC facilities in neighboring areas, thereby indicating a form of regional competition. Similarly, social welfare expenditure (SWE) shows a positive direct effect locally, while exerting a negative spillover effect on adjacent regions. This suggests that concentrating welfare resources in one area may limit the development potential in neighboring counties.

Conversely, community development and environmental protection expenditure (CEE) shows a negative direct effect, implying that increased spending in this category might crowd out local investment in long-term care facilities. Nevertheless, it yields a positive indirect effect, suggesting favorable externalities to nearby regions—such as improved living environments and infrastructure—which could attract the establishment of new care institutions in those areas.

Regarding aging variables, the elderly population ratio (PEP) demonstrates a significant negative direct effect on the number of local LTC facilities, but a strong positive spillover effect on neighboring counties or cities. This indicates that as local demand increases due to population aging, the unmet needs may spill over to nearby regions, thereby stimulating LTC facility growth in adjacent areas. In contrast, the aging index (AGI) exerts a positive direct effect locally but a negative spillover effect on neighboring areas, possibly reflecting a concentration of resources or competition for facility locations.

As for the number of approved low- and middle-income elderly living allowances (NLMA), this variable positively affects the number of LTC facilities within the local area, while exerting a negative spillover effect on neighboring counties. This may be due to the concentration of government subsidies in specific locations, which potentially weakens the motivation of private institutions to invest in nearby areas or causes resource crowding-out.

An analysis of the total effects shows that an increase in the elderly population ratio (PEP) has a positive overall impact on the number of LTC facilities, confirming that aging is a significant driver of demand for long-term care services. Conversely, the increase in the number of approved low- and middle-income elderly allowances exerts a negative total effect, indicating that excessive reliance on government subsidies might hinder private-sector expansion.

In summary, by decomposing the effects using the Spatial Durbin Model, this study effectively reveals the heterogeneous and spatial nature of the impact of fiscal expenditures and aging indicators on the distribution of LTC facilities. The findings underscore the importance of spatial spillover effects in public policy and long-term care resource allocation and provide a scientifically grounded reference for future policy formulation.

Table 9: Direct, indirect, and total effects of SDM with random-effects

Variables	Direct Effect		Indirect Effect		Total Effect	
	Coef.	Std. Err.	Coef.	Std. Err.	Coef.	Std. Err.
EDE	0.001***	0.000	-0.001***	0.000	0.000	0.000
SWE	0.001***	0.000	-0.001***	0.000	0.000	0.000
CEE	-0.002**	0.001	0.001*	0.001	0.000	0.001
PEP	-3.636***	0.810	8.112***	1.010	4.476***	0.871
AGI	0.151***	0.038	-0.242***	0.051	-0.091	0.057
NLMA	0.002***	0.000	-0.004***	0.000	-0.003***	0.000

Note: * p<0.05; ** p<0.01; *** p<0.001
Coef.:Coefficient.
Std. Err.: Standard error.
NLCNH: Number of Long-term Care and Nursing Homes, EDE: Economic Development Expenditure (in million NTD), SWE: Social Welfare Expenditure (in million NTD), CEE: Community Development and Environmental Protection Expenditure (in million NTD), PEP: Proportion of Elderly Population (65 and above) (%), AGI: Aging Index (%), Number of Approved Low- and Middle-Income Elderly Living Allowances (persons).
NTD: New Taiwan dollar (equal to USD 0.030).

5. Conclusions and Policy Implications

5.1 Research conclusions

This study employs the Spatial Durbin Model (SDM) to analyze panel data from 22 counties and cities in Taiwan between 2000 and 2023, exploring the effects of fiscal expenditure and population aging on the number of long-term care (LTC) facilities. The results demonstrate that both fiscal and demographic factors significantly influence the spatial distribution of LTC institutions, with notable asymmetries in direct and spillover effects.

Regarding fiscal expenditure, both economic development and social welfare spending show significant positive effects on the number of LTC facilities within a given locality. However, these types of expenditures also produce negative spillover effects on neighboring areas, possibly due to the concentration of resources in specific regions, which crowds out development in adjacent ones. In contrast, spending on community development and environmental protection is found to suppress local LTC facility growth while generating positive spillover effects, suggesting that improving regional living environments may attract LTC investment in nearby areas.

As for demographic aging, the proportion of the elderly population is negatively associated with the number of LTC facilities in the local area but has a strong positive spillover effect on neighboring regions. This may indicate that elderly residents tend to migrate to nearby areas with better care resources. The aging index, on the other hand, has a positive effect locally but a negative impact on surrounding regions, highlighting how areas with worsening age structures tend to attract LTC resources at the expense of adjacent regions. Additionally, the number of approved low- and middle-income elderly living allowance recipients increases the number of facilities locally but negatively affects neighboring areas. This indicates that while fiscal support may improve institutional access in specific regions, it does not necessarily enhance the overall regional supply of services.

Overall, the increase in the elderly population ratio has a positive total effect on LTC facility development, reflecting growing demand in Taiwan's aging society. However, the increase in low- and middle-income elderly subsidies appears to have a negative total effect, potentially due to an increased dependency on government-supported services rather than fostering market-driven expansion. These findings underscore the importance of considering spatial effects—both direct and indirect—when designing LTC-related policies, in order to optimize resource allocation and enhance the overall effectiveness of care infrastructure development in response to population aging.

5.2 Policy implications

Based on the empirical results of this study, fiscal expenditure and the degree of population aging across Taiwan's counties and cities have significant direct effects and spatial spillover effects on the distribution of long-term care (LTC) facilities. These findings carry important implications for policy formulation. To promote the balanced development of the LTC industry and effectively respond to the growing challenge of population aging, the government should adopt a multi-level and regionally coordinated policy strategy.

Regarding the allocation of fiscal resources, although economic development expenditure and social welfare expenditure positively influence the number of LTC facilities within a locality, they also exert negative spillover effects on neighboring areas by crowding out resources. Therefore, it is essential for the government to strengthen regional cooperation and avoid concentrating fiscal resources in only a few areas, which may cause resource shortages in surrounding regions. On the other hand, community development and environmental protection expenditures show positive spillover effects on neighboring areas, suggesting that improving overall living environments and infrastructure can attract LTC facilities. Thus, increased investment in these areas should be encouraged to foster joint regional development.

In addressing the aging issue, the impacts of the elderly population ratio and aging index on LTC facility distribution vary by region. Policymakers should tailor LTC strategies based on the demographic structure of each locality. In areas with a higher proportion of elderly residents, it is vital to enhance the supply of LTC services to meet rising demand. Moreover, the government should strengthen monitoring and forecasting of the aging index to ensure timely and preemptive allocation of LTC resources, thereby preventing shortages caused by accelerated aging.

Furthermore, regarding the negative spillover effects of subsidies for low- and middle-income elderly, the government should implement robust regulatory mechanisms to ensure that financial aid truly improves service quality and the well-being of the elderly. Encouraging the entry of private LTC providers into the market can foster competition, driving innovation and quality improvements. Inter-county cooperation, including joint planning and resource sharing, should also be promoted to expand service coverage and operational efficiency.

Finally, long-term LTC planning should be integrated into national and regional development strategies. Anticipating future demographic changes and incorporating them into urban planning and spatial policies will help ensure that LTC resources are sustainably allocated. Considering spatial spillover effects and fostering inter-regional collaboration can lead to the formation of a mutually supportive and complementary LTC service network.

In summary, this study demonstrates that fiscal expenditure and population aging have complex, interrelated impacts on the distribution of LTC facilities in Taiwan. Future policy planning must not only focus on local capacity building but also emphasize interregional coordination and the efficient allocation of resources to enhance the overall resilience and performance of the LTC system.

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