THE UNIVERSITY OF TEXAS AT DALLAS

Fiscal Forecast Errors in Public Health Expenditure: Based on a Spatial-Temporal Approach

Dohyo Jeong
Ph.D. Candidate
Public Policy and Political Economy

Introduction

- In Korea, expenditure forecasting is becoming more important as the proportion of **mandatory expenditures increases due to aging and welfare demand**.

- **The quality and scope of local government services** in areas such as social care, health, and education highly **depend on the accuracy of budget allocations** (Chakraborty et al., 2020; Emrich, 2023).

- Significant **expenditure forecast errors can lead to under- or over-allocation of resources** needed to provide services, reducing the efficiency and effectiveness of public services (Jones & Reitano, 2022).

Frameworks

Local government revenue and expenditure forecasts and errors

Revenue forecasts tend to be underestimated, while **expenditures tend to be overestimated**.

- It is easy for officials to make conservative estimates of revenues, mainly when revenues are limited at the local government level (Brück & Stephan, 2006; Pina & Venes, 2011; Williams & Calabrese, 2016).

Expenditure forecasting is about planning government spending and providing information about the expected costs of providing public services (Mikesell, 2018; Jones & Reitano, 2022).

- **The expenditure forecasting process** should consider factors such as population change, education, medical care, and public safety and requires an accurate **understanding of policy demand and supply** (Keehan et al., 2017).
- While research on revenue forecasting is steadily increasing, research on **expenditure forecasting is relatively rare**, often focusing on forecasting expenditures for specific government programs.

Frameworks

Determinants of Expenditure Forecast Error

- **Overly optimistic forecasts** of future fiscal conditions can **increase the risk of fiscal deficits**, while **overly pessimistic forecasts** can **lead to inefficiencies** in public policy spending and resource allocation (Chakraborty et al., 2020; Emrich, 2023).
  - **Forecasting revenue and expenditure for local government budgets is a necessary process**, and errors occurring during this process have been repeatedly mentioned in several studies (Beetsma et al., 2013; Merola & Pérez, 2013; Chakraborty et al., 2020; ElBerry & Goeminne, 2021; Emrich, 2023).
- However, previous studies have mainly analyzed the impact of specific government programs on expenditures and **lack extensive discussion of local government expenditure forecast errors**.
  - Previous studies **have not explored spatial interconnectivity** that influences the city, sub-urban area, and non-city area.

Research Design

Research Design

- Unit of Analysis: **local government in South Korea, yearly**.
- Time scope: **2008 ~ 2022 (15 years)**

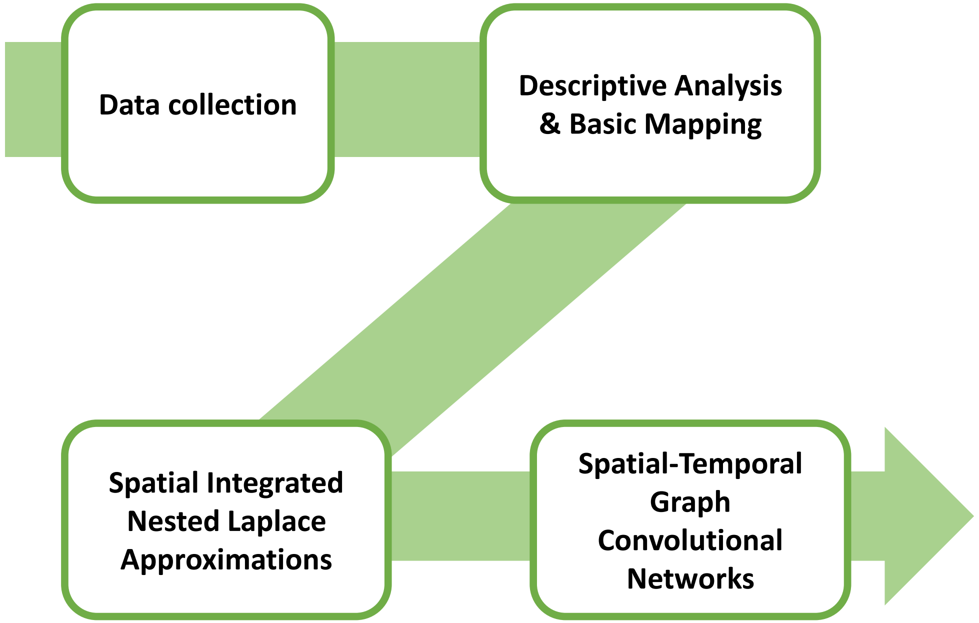
- Data Resource:

▶ **Local Finance Integrated Open System**

▶ Government Expenditure
  - social welfare expenditure, public health expenditure

- **Basic mapping** shows the spatial distribution and interconnectivity of expenditure forecast errors.
- **Spatial INLA** estimates the factors that influence Expenditure Forecasting Error.
- **Spatial-Temporal GCN** predicts future Forecasting Errors by region and time.

Data Flow



Data and Variables

Dependent variable

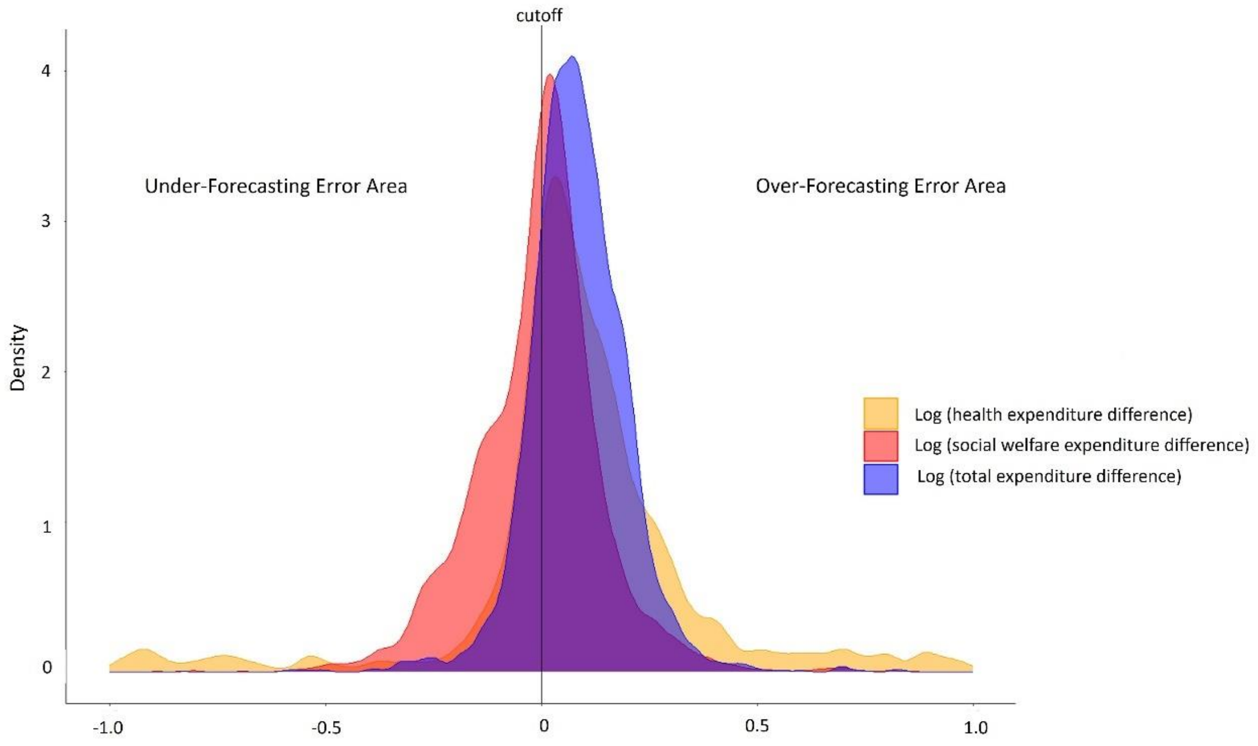
$$Expenditure\ Forecasting\ Error_i = log\left(\frac{Budgeted\ Expenditure\ Amount_i}{Actual\ Expenditure\ Amount_i}\right)$$

$$EFE\begin{cases} > 0:\ Over\ Forecasting\ Error \\ = 0: Balanced \\ < 0: Under\ Forecasting\ Error \end{cases}$$

Data and Variables

Dependent variable

Figure 1. Distribution of Forecasting Error Density Graph by Expenditure Sectors

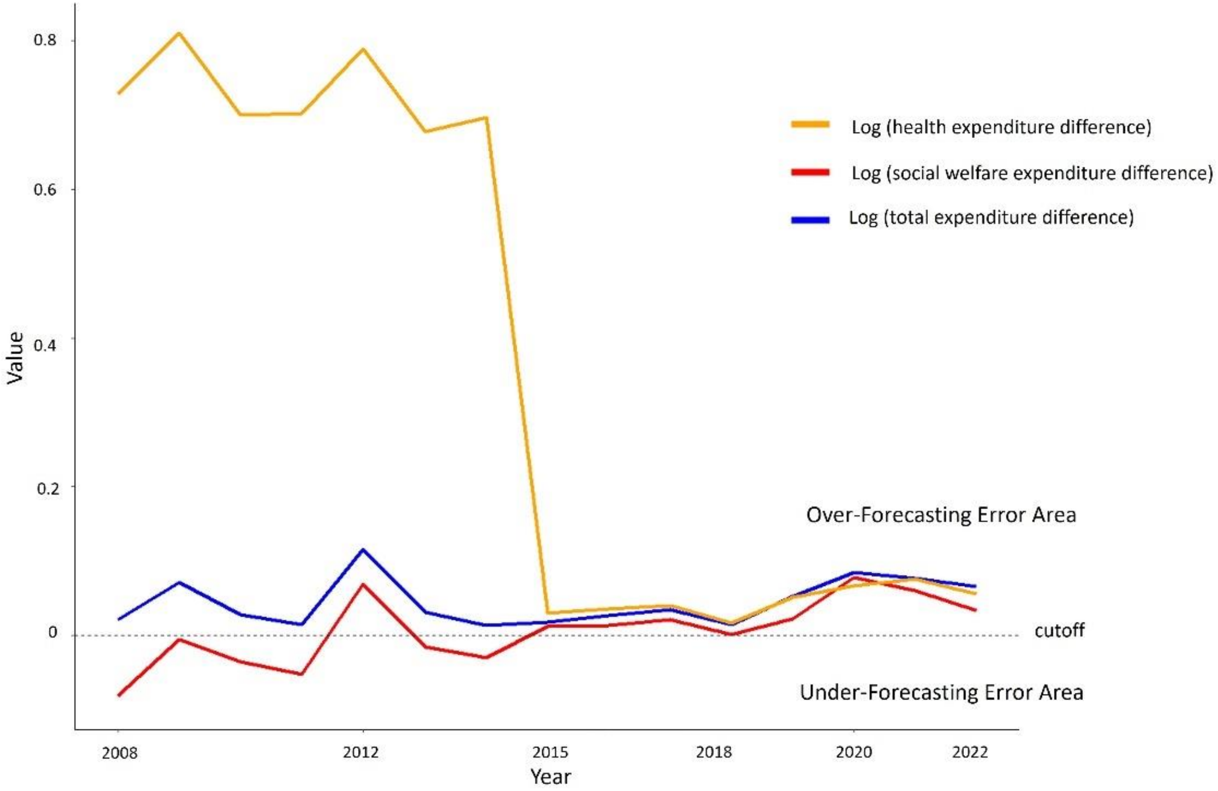


- The distribution density graph results generally reflect patterns identified in previous studies.
- Each local government tends to develop strategies to increase the possibility of fiscal surplus when it comes to spending (Williams & Calabrese, 2016; Mikesell, 2018; Jones & Reitano, 2022).

Data and Variables

Dependent variable

Figure 2. Time Trend of Forecasting Error by Expenditure Sectors



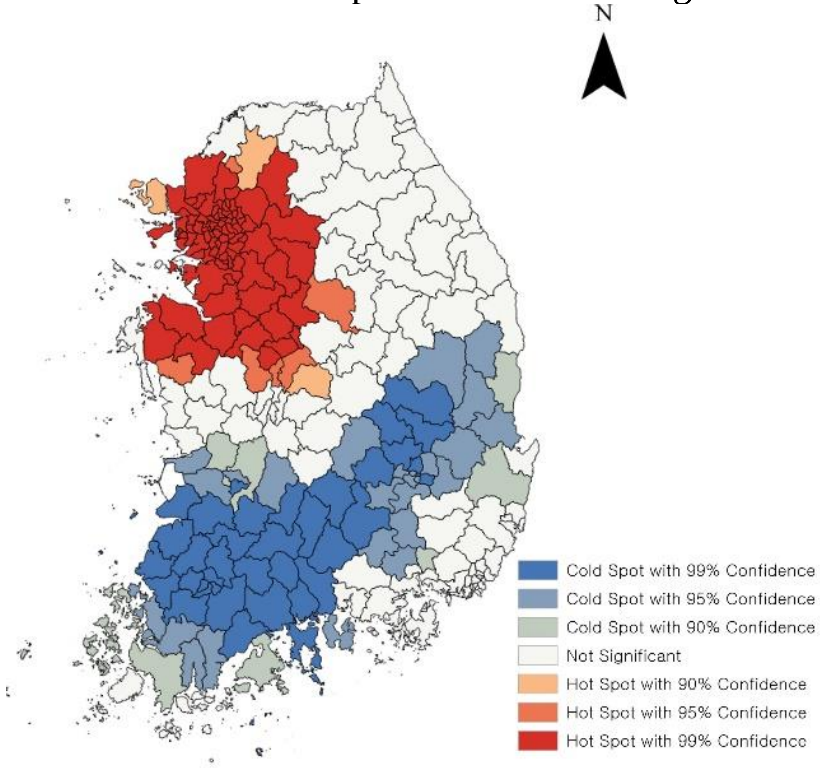
- The Korean central government revised the law to establish a systematic response system following the MERS outbreak in 2015 (Park et al., 2022).
- **local governments were able to reduce unexpected expenditures**, reducing errors in predicting medical expenses (Eissa, 2020).
- This highlights that **expenditure forecasts** in the social care and health sectors **can vary over time and are vulnerable to unexpected fluctuations** (Forni & Gambetti, 2016; Eissa, 2020).

Data and Variables

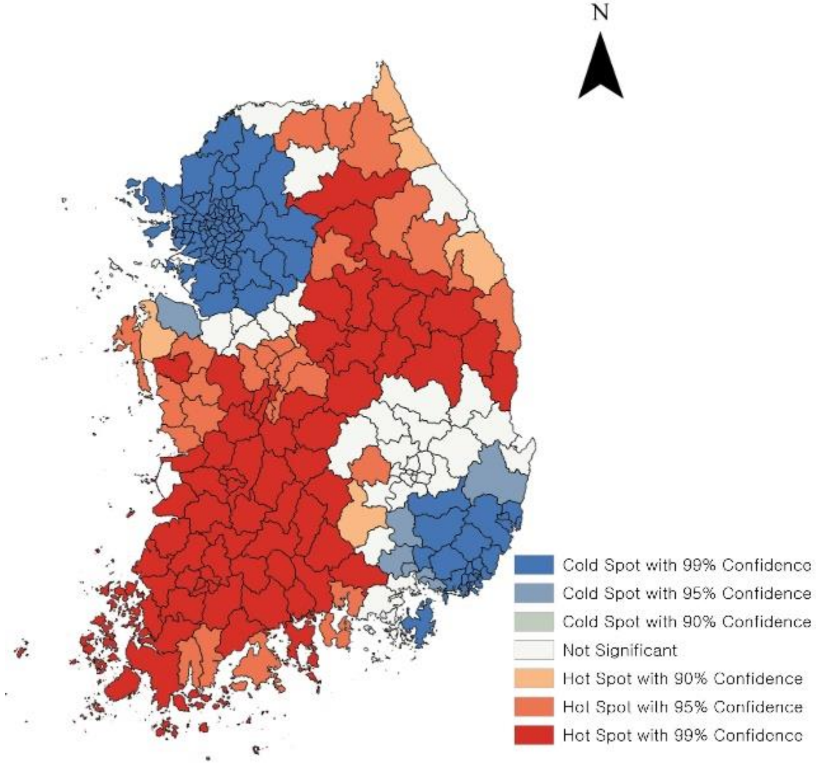
Dependent variable

Figure 3. Results of Getis-Ord Gi* Hotspot for Expenditure Forecasting Error

Social Welfare Expenditure Forecasting Error



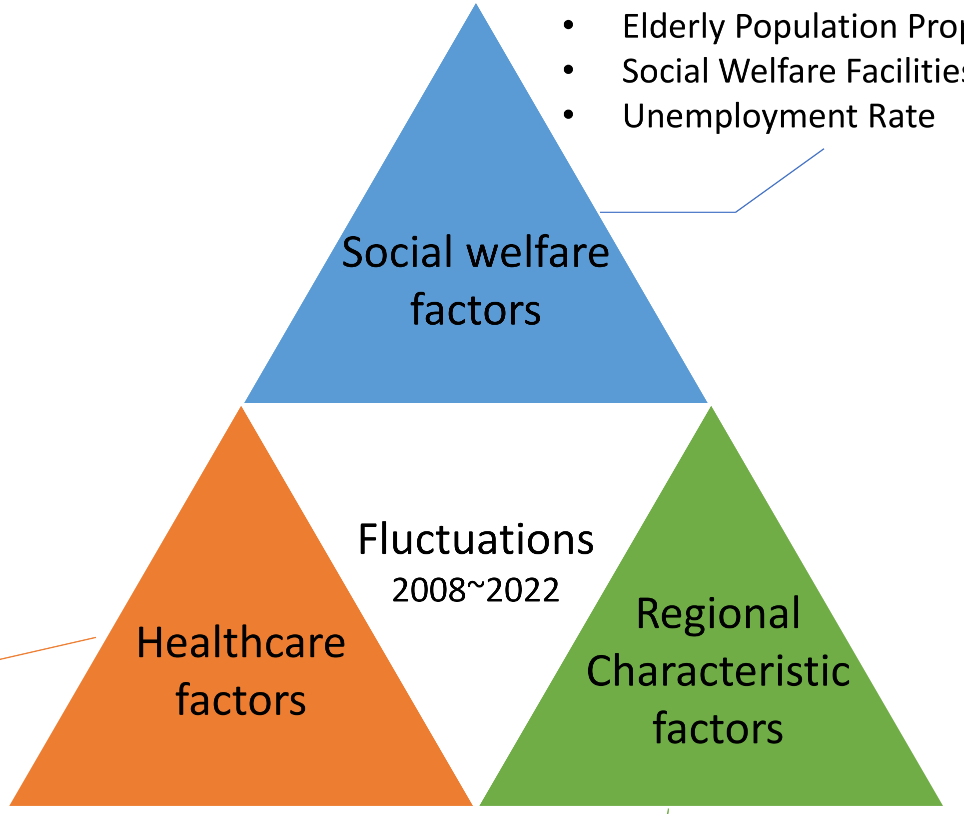
Health Expenditure Forecasting Error



Data and Variables

Independent variables

- Basic Social Welfare Rate
- Elderly Population Proportion
- Social Welfare Facilities
- Unemployment Rate



- number of Tuberculosis
- Hospital Rooms
- Population Movement
- Health Insurance Applied Population

- GRDP
- Gender ratio
- Financial Independence

- This study constructs independent variables based on **the fluctuations (standard deviation) from 2008 to 2022** (Sheng & Yao, 2014; Jurado, 2015; Kaminska & Roberts-Sklar, 2018).

- **High fluctuations indicates that the variable can fluctuate** significantly, making it difficult to accurately forecast spending in that area during the forecasting process (Kaminska & Roberts-Sklar, 2018).

Methodology

What factors influence Expenditure Forecasting Error?

Basic Linear Model

$$Y_i = \alpha_i + (\beta \cdot X)_i + \epsilon_i$$

- Y_i *:* Log Relative Risk (Imbalance) Index for county *i*
- α_{it}: intercept
- $(\beta \cdot X)_i$: interaction between the risk variables

▶ It is difficult to explain the complex relationships in each region linearly.

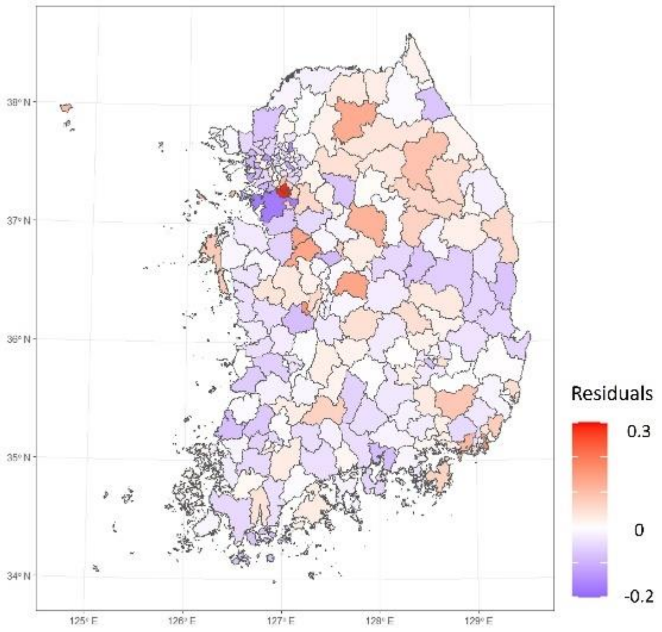
▶ Spatial autocorrelation of the error term is suspected.

Methodology

What factors influence Expenditure Forecasting Error?

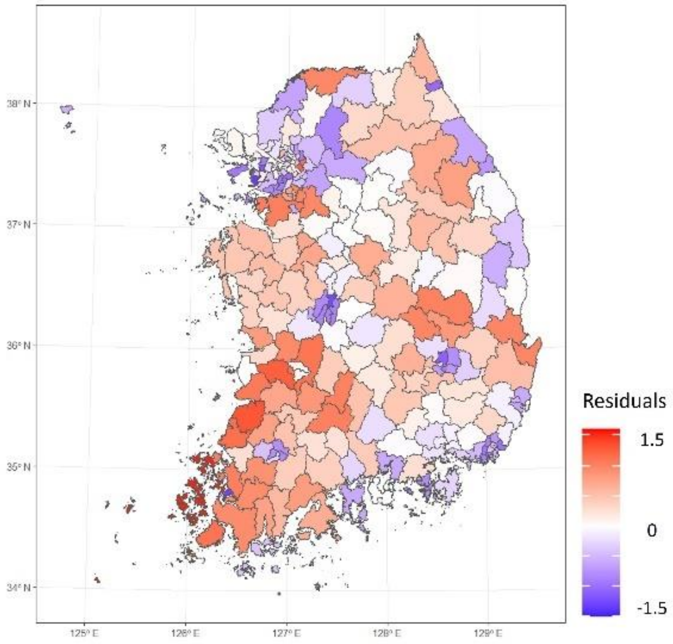
Figure 4. Moran’s I Test Results and Residual Plots

Social Welfare Expenditure Forecasting Error



Moran I: 0.307 / Moran I statistic: 8.198***

Health Expenditure Forecasting Error



Moran I: 0.465 / Moran I statistic: 12.117***

***, $p < 0.001$

Methodology

What factors influence Expenditure Forecasting Error?

Spatial INLA

$$Y_i = \alpha_i + (\beta \cdot X)_i + \theta_i^{iid} + \theta_i^{CAR} + \epsilon_i^{iid}$$

- Y_i *:* Log Relative Risk (Imbalance) Index for county *i*
- α_{it}: intercept
- $(\beta \cdot X)_i$: interaction between the risk variables
- θ_i^{iid}: county-specific random effect (independent and identically distributed)
- θ_i^{CAR}: spatially structured random effect (Conditional Auto Regressive modeling)
- ϵ_i^{iid}: *"space random interaction effect"*

So, how do we minimize and forecast spending forecast errors?

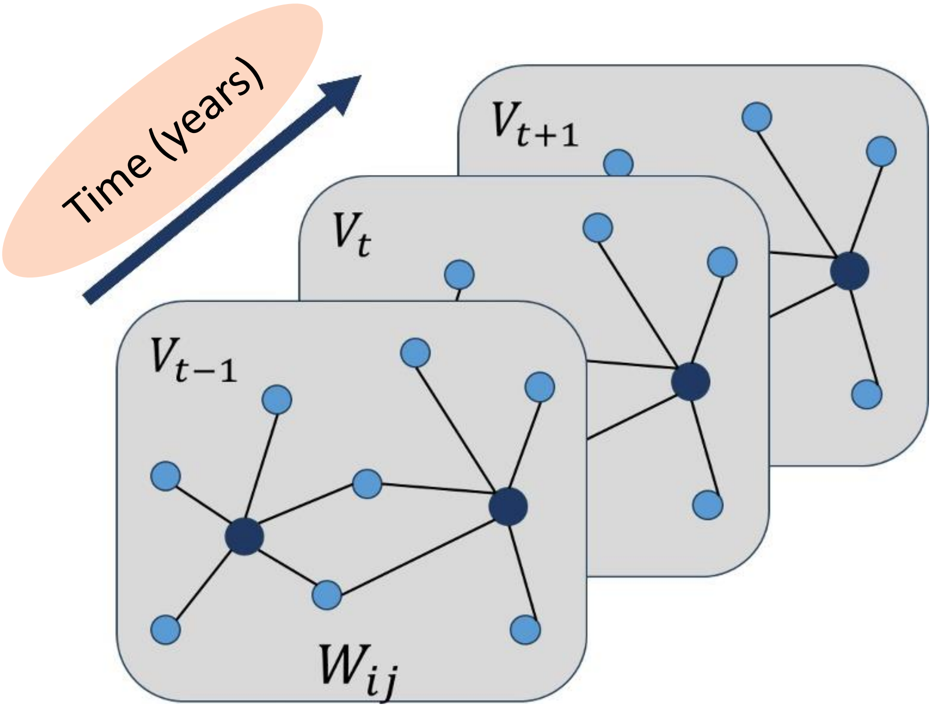
Methodology

What will happen in the future?

- The preceding mapping and graphs confirmed that **expenditure prediction errors are affected by region and time**.

- When building a machine learning model to predict spending forecast error, we need a model that considers both temporal and spatial aspects.

Figure 5. Basic Model of Spatial-Temporal Graph Convolutional Networks



w_{ij} : *Spatial adjacency matrix between region i and region j*

v_t : *Vector (v) connection structure of each region recorded at time t*

Source: Reorganized from Yan et al., 2018; Xiao et al., 2021; Zhao et al., 2023

Results

Descriptive Analysis

Table 1. Results of Descriptive Analysis

		Obs	Mean	Std. dev.	Min	Max
Year		3,705	2015	4.32	2008	2022
Log(Total difference)		3,705	0.09	0.15	1.60	2.25
Log(Social welfare difference)		3,705	0.01	0.17	-1.29	2.21
Log(health difference)		3,705	0.24	1.52	-5.51	3.72
Social Factors	BSWelR	3,705	0.04	0.02	0.01	0.52
	Elder	3,705	18.02	8.36	4.70	44.30
	SWFac	3,705	16.53	11.12	0.30	76.60
	UnRate	3,705	3.24	0.81	1.60	5.00
Medical Factors	TB	3,705	21.04	21.63	0.15	172.85
	HospRm	3,705	13.62	8.62	0.00	70.10
	HIAppP	3,705	291.62	88.19	40.43	489.44
	PopMov	3,705	-0.05	6.18	-21.78	72.03
Socioeconomic factors	GRDP	3,705	31356.5	8157.0	16826.0	60971.0
	Pop	3,705	280.66	286.13	16.02	1202.63
	Gender	3,705	100.53	4.91	88.40	133.00
	FIndep	3,705	28.60	15.69	6.40	86.00
	FAuton	3,705	61.35	11.27	21.90	91.80

Results

Descriptive Analysis

Table 2. ***Fluctuations (standard deviation)*** for Each Variable from 2008 to 2022

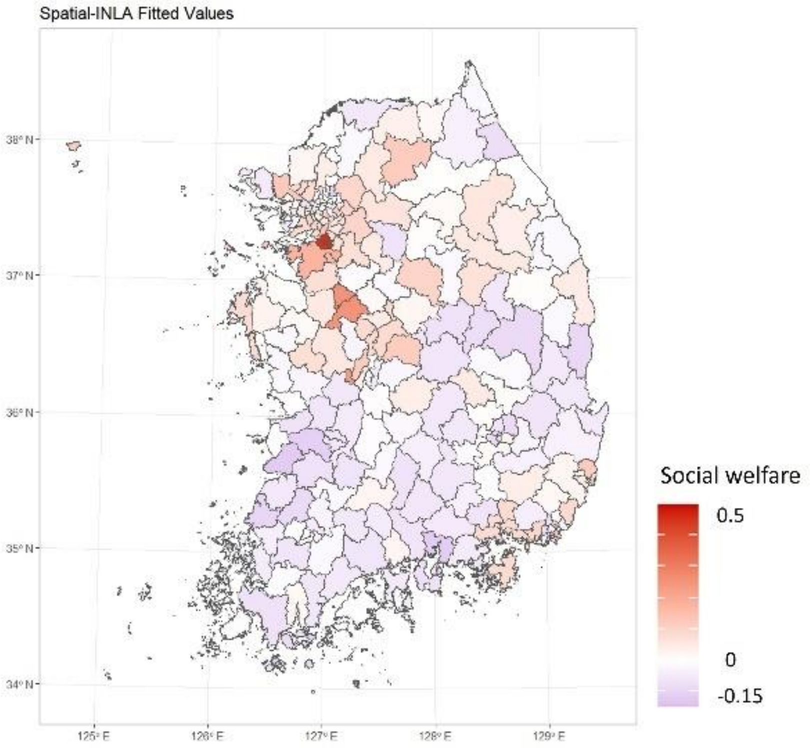
		Obs	Mean	Std. dev.	Min	Max
Social Factors	BSWelR	247	0.01	0.008	0	0.13
	Elder	247	2.88	0.87	0.56	5.56
	SWFac	247	3.90	2.62	0.3	15.45
	UnRate	247	0.46	0.11	0.28	0.71
Medical Factors	TB	247	4.95	4.63	0.39	26.55
	HospRm	247	2.28	1.87	0.1	13.63
	HIAppP	247	26.30	12.99	4.27	104.26
	PopMov	247	2.84	3.26	0.11	23.36
Socioeconomic factors	GRDP	247	5571.18	1196.68	3777.73	7412.42
	Pop	247	16.28	23.46	0.29	159.40
	Gender	247	0.98	0.74	0.16	6.65
	FIndep	247	3.55	2.20	0.71	18.41
	FAuton	247	4.20	2.02	1.17	10.43

Results

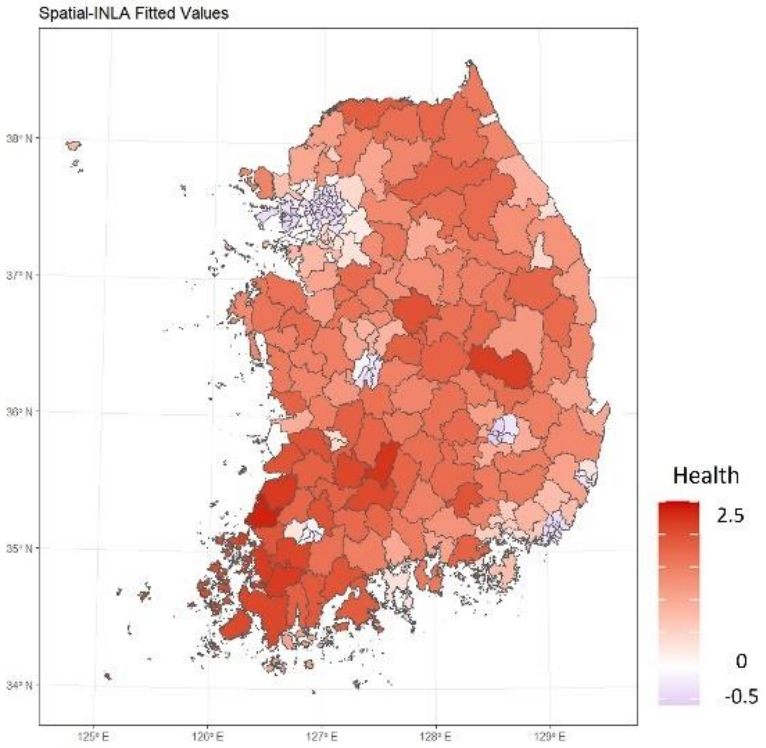
Spatial INLA

Figure 6. Spatial INLA Fitted Values for Expenditure Forecast Errors by Sector

Social Welfare Expenditure Fitted Values



Health Expenditure Fitted Values



Results

Spatial INLA

Spatial INLA		Social Welfare Expenditure Forecasting Error				Health Expenditure Forecasting Error			
		Mean	Sd	LB	UB	Mean	Sd	LB	UB
	Intercept	-1.110	0.451	-1.993	-0.222	0.558	3.472	-6.256	7.373
Social Factors	BSWelR	-2.334	0.587	-3.485	-1.181	-3.730	4.060	-11.69	4.240
	Elder	-0.012	0.006	-0.024	0.001	-0.072	0.042	-0.155	0.011
	SWFac	0.001	0.002	-0.002	0.005	0.047	0.012	0.023	0.070
	UnRate	0.016	0.067	-0.118	0.147	0.904	0.514	-0.105	1.913
Medical Factors	TB	0.002	0.001	0.001	0.004	0.025	0.007	0.012	0.039
	HospRm	-0.001	0.003	-0.006	0.004	-0.001	0.017	-0.035	0.033
	HIAppP	-0.002	0.001	-0.002	-0.001	0.001	0.002	-0.005	0.005
	PopMov	0.005	0.002	0.001	0.10	-0.005	0.017	-0.038	0.027
Soci-Economy Factors	GRDP	0.134	0.051	0.034	0.233	0.014	0.389	-0.749	0.777
	Pop	0.001	0.001	0.000	0.001	0.001	0.002	-0.003	0.004
	Gender	-0.002	0.007	-0.015	0.011	0.021	0.050	-0.076	0.119
	FIndep	0.004	0.003	-0.002	0.010	0.035	0.021	-0.005	0.076
	FAuton	0.005	0.003	-0.001	0.011	-0.128	0.023	-0.174	-0.083
countyIID		1009.6	345.51	493.6	1842.5	537.3	672.8	64.8	2273.2
IID compoenet		3131.0	1723.3	1043.3	7650.0	2011.6	1904.8	179.2	7088.5
Spatial component		147.05	34.43	89.03	223.97	1.38	0.13	1.14	1.65
		DIC: -1472.49 WAIC: -1512.70 Marginal log-Likelihood: 279.58				DIC: -1434.42 WAIC: -1461.69 Marginal log-Likelihood: -188.20			

LB: Lower Bound (0.025quant); UB: Upper Bound (0.975quant)
DIC: Deviance information criterion; WAIC: Widely applicable Bayesian information criterion
VIF (Variance Infloation Factor): 1.93

Social Welfare Expenditure Forecasting Error

Over forecasting

Fluctuations of

- number of Tuberculosis
- Population Movement
- GRDP

Under forecasting

Fluctuations of

- Basic Social Welfare Rate
- Health Insurance Applied

Healthcare Expenditure Forecasting Error

Over forecasting

Fluctuations of

- Social Welfare Facilities
- number of Tuberculosis

Under forecasting

Fluctuations of

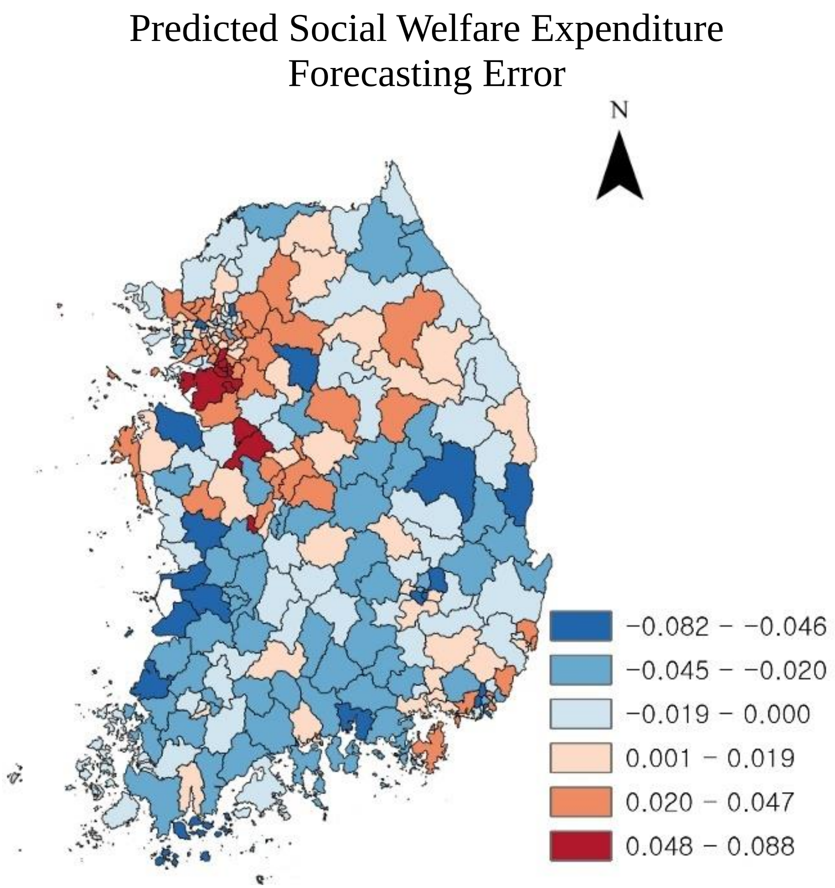
- financial autonomy

▶ ***So, to prepare for the future, what pattern of forecast errors will each region experience?***

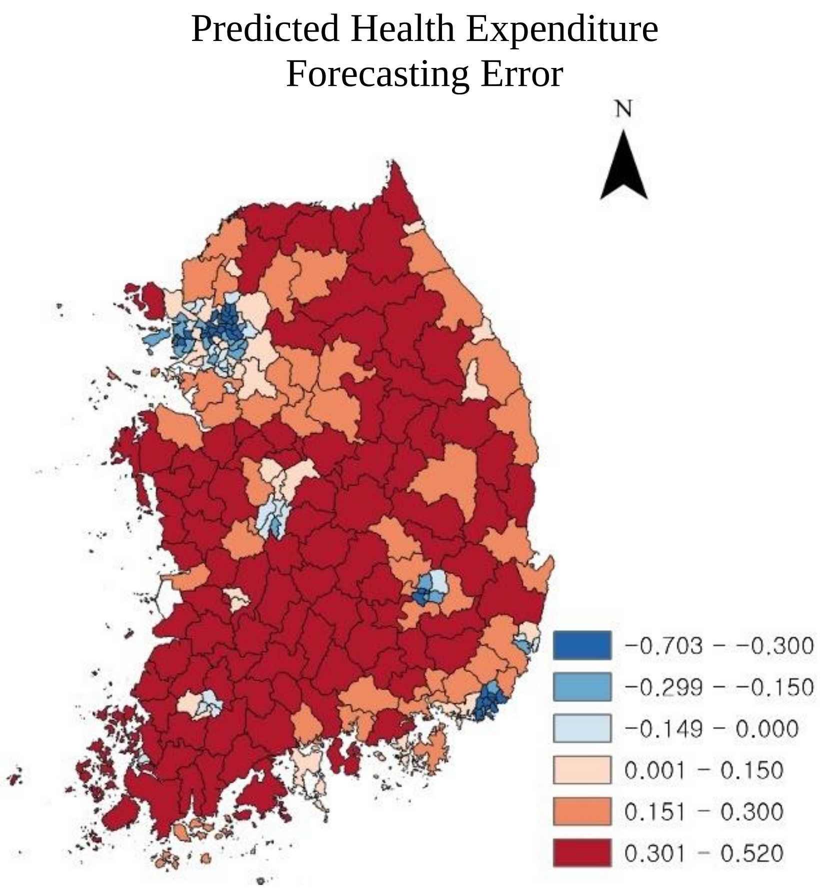
Results

Spatial-Temporal Graph Convolutional Networks

Figure 7. Expenditure forecast error prediction results based on ST-GCN



MAE: 0.019955 | RMSE: 0.029127



MAE: 0.0114518 | RMSE: 0.165469

Discussion

Impact of spatial-temporal patterns

- The analysis shows that **temporal factors and spatial patterns are important in understanding local government expenditure forecast errors** in social welfare and health sectors.

- In particular, the clear spatial pattern of expenditure forecast errors suggests the **need to consider differences and interactions between regions**.

Contrasting Results in Social Welfare and Public Health Sectors

- **Metropolitan and non-metropolitan areas may differ in their social welfare and healthcare needs**, which affects budget allocation (Allers & De Greef, 2018; Spreen & Martinez Guzman, 2022).

  - Expenditure forecast errors between urban and non-urban areas can be interpreted as the result of interactions.
  - Increasing aging population and disease rates affect the demand for social welfare and medical services, which increases budget forecast errors.

Conclusion

Conclusion

- Key findings support previous findings that **social, health, and socio-economic fluctuations** at the local government level play an **essential role in expenditure forecast errors**, emphasizing the **need to consider spatial interactions and temporal changes**.

- However, the study used data from 2008 to 2022, which may not be sufficient to identify and predict determinants and did not sufficiently control for the impact of health crises such as MERS and COVID-19.

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