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ORIGINAL RESEARCH

The Transmission of Nurse Employment Spillovers and Their Impact on Inpatient Care Quality: A Dynamic Connectedness Network Analysis

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Purpose: This study examines the intersectoral interdependencies of nurse employment, conceptualized as nurse employment spillovers, and their effects on inpatient care quality in Taiwan. It particularly addresses the critical issue that over 40% of Taiwanese nurses report unwillingness to enter or remain in the nursing profession.

Methods: The research design follows a quantitative and observational time-series methodology. A time-series dynamic connectedness network analysis was employed to assess interdependencies in nurse employment across various practice settings. Additionally, a general-to-specific modeling approach was used to examine the relationship between the transmission of nurse employment spillovers and inpatient care quality. The analysis utilized annual data from 1997 to 2023, comprising 27 observations, sourced from publicly available Taiwanese government databases that contain information on nurse employment, inpatient care quality indicator, and relevant control variables.

Results: The analysis reveals that nurse employment in other healthcare facilities and the non-nursing labor market (hospitals, clinics, and long-term care facilities) serves as a net transmitter (receiver) of nurse employment spillovers. Notably, nurse employment inflows from non-nursing to nursing labor markets are linked to enhancements in inpatient care quality. Five distinct spillover pathways originating from clinics, other medical institutions, and non-nursing sectors into hospitals were identified as having positive effects on inpatient care quality. Furthermore, increases in nurses' regular wages are associated with a shift in employment toward hospital settings.

Conclusion: These findings underscore the importance of strengthening hospital nurse employment to improve inpatient care quality. Policymakers should consider salary increases as a means to attract and retain nurses in the healthcare sector, thereby mitigating shortages of nurses and enhancing care outcomes.

Keywords: connectedness network analysis, extended joint connectedness approach, nurse employment behavior, nurse shortage, inpatient care quality, 14-day readmission rate

Introduction

Background

According to the State of the World's Nursing 2025 report, the global nurse shortage was estimated at 5.8 million in 2023, with nearly 70% concentrated in Africa and the Eastern Mediterranean.[1] A recent meta-analysis of 21 studies spanning 14 countries reported a global nurse turnover rate of 16%, with higher rates in Asia (19%) and lower rates in North America (15%).[2] These regional disparities, shaped by economic, cultural, and health system factors, underscore the urgent need for context-specific strategies to strengthen workforce stability and highlight the persistent nurse shortage

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as a critical threat to the sustainability of healthcare systems and their ability to deliver high-quality care.[1–3] Extensive evidence indicates that that nurse staffing shortages are associated with an increased risk of patient mortality[4–8] and higher incidences of nursing-sensitive quality indicators such as patient falls, medication errors, pressure ulcers, the use of physical restraints, and healthcare-associated infections.[4,6,8] Furthermore, inadequate nurse staffing hinders the effective monitoring and reporting of adverse events,[9,10] compromises overall care quality and patient satisfaction,[11–13] and contributes to unfavorable outcomes such as prolonged hospital stays, higher readmission rates, and a rise in emergency department utilization.[4,5,7,14,15]

It is important to note that studies investigating the relationship between nurse staffing levels and the quality of care often oversimplify the input–output relationship in hospital production, treating nursing manpower as a key input and quality indicators as direct outputs.[16] Nevertheless, from the perspective of nursing workforce distribution, hospital nurse staffing levels are not determined by exogenous factors but are due to nurses' endogenous employment choices across various practice settings, such as hospitals, clinics, long-term care (LTC) facilities, other healthcare facilities, or non-nursing roles. These employment behaviors are interdependent and dynamically interconnected, collectively shaping how nursing resources are allocated across healthcare sectors. The lack of modeling regarding nurses' movements across different practice settings—and the interdependent dynamics involved, referred to as nurse employment spillovers—has contributed to the persistent challenges in addressing nursing shortages. As a result, policymakers have narrowly focused on hospital-based staffing interventions, rather than adopting comprehensive, system-wide workforce strategies.

Prior research has largely relied on static input measures, such as patient-to-nurse ratios (PNRs), to assess nursing effects on inpatient care.[4–15,] Nevertheless, the dynamic transmission of nurse employment spillovers across the healthcare system remains unexamined, leaving critical gaps in understanding how these intersectoral dynamics influence care quality. This study addresses this research gap from a workforce planning perspective under the critical nurse shortages globally with 4.1 million nurses lacking by 2030—mostly in Africa and the Eastern Mediterranean—and high turnover rates, particularly in Asia, underscoring the need for targeted workforce strategies to sustain healthcare quality.[1,2] In this study, we particularly focus on Taiwan for three main reasons: First, Taiwan's nursing labor market faces a severe challenge—more than 40% of licensed nurses are either unwilling to enter or reluctant to remain in the profession.[17] This phenomenon persists despite a series of policy and institutional interventions, including mandated minimum PNRs, the incorporation of PNRs as key indicators in hospital accreditation, direct salary increases for night shift nurses, incentive programs for hospitals that meet PNR targets across day, evening and mid-night shifts, the recognition of the need for nurse-friendly workplaces, and the implementation of clinical mentorship systems for newly graduated nurses.[18,19] Second, Taiwan is rapidly becoming a hyper-aged society (as of 2025), and its total fertility rate has fallen far below replacement levels.[20] This demographic trend not only increases the demand for nurses in hospitals but also reduces the future labor supply. As a result, the shortage of nurses is projected to reach between 55,000 and 74,000 by 2030.[21] Third, Taiwan's healthcare system operates under a single-payer National Health Insurance program that provides universal coverage. This system is supported by a comprehensive, population-level claims database—the National Health Insurance Research Database (*NHIRD*)—which contains consistent time-series data on healthcare utilization and patient outcomes, making it a crucial resource for healthcare quality surveillance in hospitals. Collectively, these conditions offer a robust contextual foundation for investigating the transmission of nurse employment spillovers and their effects on the quality of inpatient care.

Aims of the Study

To examine the link between nurse employment spillover transmission and inpatient care quality, this study addresses three key research questions: (1) How can the transmission of nurse employment spillovers be identified and modeled? (2) Is there a significant relationship between the transmission of nurse employment spillovers and inpatient care quality? (3) Do nurses' wages play a pivotal role in shaping the transmission of nurse employment spillovers? Accordingly, this study has three primary objectives. First, it employs a dynamic connectedness network analysis using the time-varying parameter vector autoregressive (TVP-VAR) extended joint connectedness approach[22] to capture the evolving inter-relationships within the nurse employment behavior network. It specifically focuses on nurses' employment choices across diverse practice settings, including hospitals, clinics, LTC facilities, other healthcare facilities, and non-nursing roles. This method facilitates the estimation of sector-specific and total nurse employment spillover metrics, quantifying the directional diffusion of employment flows within and across sectors. Second, the general-to-specific (GETS) modeling approach[23] is utilized to examine the relationship between the transmission of nurse employment spillovers and inpatient care quality. Third, given that wage increases have been implemented by the Taiwanese government to attract and retain nurses in the healthcare sector, this study further investigates whether changes in nurses' regular monthly wages contribute to spillover effects within the nurse employment behavior network.

Literature Review

The use of network analysis methodologies has increased in healthcare research due to their capacity to examine relational dynamics such as collaboration, coordination, and interdependent activities among healthcare entities.[24] In the context of nursing research, network analysis has been adopted across several domains, including team communication, consultation networks, and their relationship with quality of care;[25–27]workplace stress, team performance, and job satisfaction;[28–30] professional roles and the public image of nurses;[31–33] knowledge dissemination practices;[34,35] research collaboration;[36,37] and nursing education and students' psychological well-being.[38–40] These numerous applications highlight the analytical value of network-based approaches in addressing complex, systemic issues within the nursing and broader healthcare fields.

Although network analysis has been widely utilized in nursing research, prior studies exhibit notable methodological limitations. First, their heavy reliance on small-sample and cross-sectional designs introduces potential endogeneity bias due to the inherent interdependence among healthcare entities.[24] Second, the lack of time-series frameworks has resulted in static analyses that fail to capture dynamic interrelationships, particularly in the context of unobserved structural changes in organizational or individual preferences and behaviors.[41,42] In response to these limitations, this study adopts a dynamic connectedness network analysis based on the TVP-VAR extended joint connectedness approach.[22] Grounded in generalized forecast error variance decomposition, this method treats all variables as endogenous, enabling the modeling of mutual interdependencies among nurses' employment choices across various practice settings. The model's time-varying structure means it can accommodate structural shifts in the data-generating process. As such, the TVP-VAR extended joint connectedness approach offers a robust method for simultaneously examining endogeneity and structural change to analyze nurse employment dynamics.

Contributions of This Study

This study contributes to the existing literature on the relationship between nurse staffing and care quality in two key ways. First, it quantifies system-wide nurse employment spillovers using connectedness indices derived from the nurse employment behavior network,[22] further investigating the extent to which nurses' wages serve as a key determinant of nurse employment spillovers within this network. Second, it applies the GETS modeling approach—a machine learning-based, auto-selective method optimized for the goodness of fit[23]—to assess the effects of nurse employment spillover transmission on inpatient care quality. This approach contrasts with those used in previous studies that have predominantly examined the direct effects of hospital nurse staffing levels on healthcare quality.[4–15] The findings of this study offer a system-wide perspective on nurse workforce dynamics and offer empirical evidence to inform strategies aiming to monitor and stabilize care quality across the healthcare system.

Materials and Methods

Research Design

The research design follows an observational time-series methodology, employing secondary data for empirical analysis. This study is a quantitative time-series analysis, rather than a cohort, case-control, or cross-sectional study. It adheres to the STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) guidelines,[43] with the completed EQUATOR checklist provided in Table S1. Specifically, we adopt the TVP-VAR extended joint connectedness approach,[22] along with the GETS modeling approach,[23] to examine the relationship between the transmission of nurse employment spillovers and inpatient care quality. The empirical approaches employed in this study offer distinct methodological advantages. The TVP-VAR extended joint connectedness approach addresses endogeneity by treating all variables as endogenous, thereby modeling mutual interdependencies across practice settings.[22] Its time-varying structure captures dynamic relationships and accommodates structural shifts in the data-generating process (eg, the COVID-19 pandemic),[22] making it well-suited for evolving healthcare contexts. Complementing this, the GETS modeling approach provides flexibility in variable selection, reduces model uncertainty through encompassing tests, and benefits from recent advances in automation and machine learning that enhance efficiency while minimizing subjective bias.[23]

Data Analysis

The empirical procedure used in this study consists of three steps. First, we assess the transmission of nurse employment spillovers within the nurse employment behavior network by estimating sector-specific and total nurse employment spillover metrics using the TVP-VAR extended joint connectedness approach.[22] Second, we employ the GETS modeling approach[23] to examine the relationship between nurse employment spillover transmission and inpatient care quality. Third, we study the extent to which nurses' wages influence the transmission of nurse employment spillovers within the nurse employment behavior network.

Conceptualizing Nurse Employment Spillovers

Moreover, we define the nurse employment behavior network based on transitions across diverse practice settings—including hospitals, clinics, LTC facilities, other healthcare facilities, and non-nursing roles—and conceptualize the intersectoral interdependencies of nurse employment as nurse employment spillovers. The TVP-VAR extended joint connectedness framework generates three key spillover measures: the Total Connectedness Index (*TCI*), the Net Total Directional Connectedness Index ($NTDCI_i$), and the Net Pairwise Directional Connectedness Index ($NPDCI_{i \to j}$). The *TCI* quantifies the overall degree of interconnectedness across the entire network, while the $NTDCI_i$ indicates whether sector i is a net transmitter or receiver of employment shocks, where a positive value implies that nurse employment in sector i affects the rest of the network and a negative value indicates that it is predominantly influenced by it. The $NPDCI_{i \to j}$ captures the directional spillovers from sector i to sector j, with positive values indicating the presence of such transmissions.

GETS Modelling

This study investigates the relationship between the transmission of nurse employment spillover and inpatient care quality using the GETS modeling approach,[23] with a 14-day readmission rate set as the dependent variable. The model includes both always-included regressors (ie, the number of general hospital beds and average length of stay) and a pool of candidate regressors representing various nurse employment spillover metrics. Once the relationship between nurse employment spillover transmission and inpatient care quality is established, we further investigate the role of nurses' wages in driving these spillovers within the nurse employment behavior network. The technical details of our empirical models are provided in the Supplementary Materials.

Data Sources

The data used for the dynamic connectedness network analysis consist of five time series representing nurse employment across distinct practice settings: hospitals (HP), clinics (CL), LTC facilities (LC), other healthcare facilities (OH), and non-nursing roles (NE). The LTC facilities (LC) include nursing homes and mental health rehabilitation institutions. Other healthcare facilities (OH) encompass a broad range of settings, including other medical institutions (eg, blood donation centers, pathology centers) and medical care institutions (eg, midwifery, physical therapy, radiology, psychological counseling, speech therapy, dental laboratories, optometric services, nutrition counseling) and non-medical care facilities (eg, school and workplace dispensaries, social welfare institutions, mental health departments, nursing education instructors). The annual data for HP, CL, LC, and OH were sourced from the *1997–2023 Report on Medical Care Institution Utilization*, published by Taiwan's Ministry of Health and Welfare (MOHW). The NE series is derived by subtracting the total number of practicing nurses (ie, the sum of HP, CL, LC, and OH) from the total number of licensed nurses. The data on the total number of licensed nurses for the period 2005–2023 were obtained from the *2005–2023 Monthly Nurse Statistics in Taiwan*, administered by the Taiwan Union of Nurses Association. To estimate the total number of licensed nurses prior to 2005, a backward forecasting method was employed, starting from the 2005 benchmark and subtracting the number of newly licensed nurses at year *t* from the total number at year *t*. The data on newly licensed nurses were drawn from the *2005–2023 Statistics of General Health and Welfare*, also published by Taiwan's MOHW.

Since nurse employment spillovers were generated using first-differenced nurse employment data, only 26 annual observations (covering the period from 1998 to 2023) were used to estimate the dynamic input–output relationship specified in the hospital production function. Inpatient care quality was evaluated using the 14-day readmission rate, derived from the *NHIRD*. This rate is calculated as the number of readmissions occurring within 14 days of discharge divided by the total number of admissions. Hospital capital input was assessed according to the number of general hospital beds per 10,000 population, obtained from the *Macroeconomic Statistics Database* maintained by Taiwan's Directorate General of Budget, Accounting and Statistics. Patient severity was measured by the average length of stay per admission, derived from the *1998–2023 National Health Insurance Annual Statistical Reports*. As indicated in the established nurse labor supply literature,[44] wages were hypothesized to influence nurse employment spillovers. The data on nurses' regular monthly wages from 2003 to 2023 were obtained from the *Salary Survey Dynamic Query Databas*e administered by Taiwan's Ministry of Labor. Regular monthly wage comprises salary, standard allowances (eg, rent, transportation, meals), and monthly bonuses (eg, performance, attendance), excluding non-monthly payments such as overtime, holiday, year-end, or unused vacation bonuses. To estimate regular monthly wages for nurses during the period 1998–2003, a linear backward forecasting method was applied, using regular monthly wage data for female health workers from 1998 to 2023 (sourced from the *Macroeconomic Statistics Database*) as the predictor.

Ethical Considerations and Sample Collection

This study utilized secondary data, including annual time-series information on aggregate nurse employment across sectors, average nurse wages, average hospital beds in Taiwan, and overall inpatient care utilization without involving any individual-level data. Consequently, the use of aggregate data poses no ethical concerns. All data sources are publicly accessible online, except for inpatient care quality data (measured by the 14-day readmission rate), which were obtained from the *NHIRD* through the SAS Academic Software; access to these data requires formal application and approval. The study period spans 1997 to 2023, providing 27 annual observations.

Results

The first two subsections (Static and Dynamic Connectedness Network Analysis) address the study's first primary objective by using the TVP-VAR extended joint connectedness approach [22] to capture evolving interrelationships within the nurse employment network. The subsequent subsection (Employment Spillovers and Inpatient Care Quality) addresses the second primary objective, employing the GETS modeling approach [23] to examine the relationship between nurse employment spillovers and inpatient care quality, as well as the third objective concerning the role of wages in influencing spillover pathways.

Static Connectedness Network Analysis

Panels A and B of Table 1 present the descriptive statistics and KPSS unit root tests[45] for the five time series representing nurse employment across distinct practice settings (see Figures 1A–F for the corresponding time plots). Due to space limitations, a detailed discussion of these results is provided in the Supplementary Materials. Panel C of Table 1 presents the static connectedness network matrix derived using the TVP-VAR extended joint connectedness approach.[22] This matrix summarizes the interrelationships among the five nurse employment time series across distinct practice settings. The ij^{th} element of the matrix indicates the estimated contribution of shocks to nurse employment in sector j to the forecast error variance of nurse employment in sector i. The sum of the off-diagonal elements in each row quantifies the directional spillovers received by nurse employment in sector i from all other sectors, while the sum of the off-diagonal elements in each column captures the directional spillovers transmitted from sector j to all other sectors. The net total directional connectedness index (*NTDCI*) is calculated as the difference between these two sums for each sector, indicating whether a sector is a net transmitter or receiver of employment shocks within the network. The total

Table 1 Descriptive Statistics and Static Connectedness Network

A. Descriptive Statistics					
Var	Description (Unit: 1000 Person)	Mean	SD	Min	Max
HP	Total number of licensed nurses employed in hospitals	89.290	21.363	55.250	120.002
CL	Total number of licensed nurses employed in clinics	20.221	7.906	7.624	34.581
LC	Total number of licensed nurses employed in LTC facilities	4.412	2.500	0.624	8.020
OH	Total employment of licensed nurses in other healthcare facilities	14.125	6.121	6.133	25.741
NE	Total number of licensed nurses not engaged in the nursing labor market.	95.470	24.538	42.128	131.250

B. KPSS Unit Root Test					
Var	Tend T-stat	Bootstrap p value	Specification Test	Level	1st Difference
ln(HP)	35.139	0.00**	Constant+Trend	0.520**	0.079
ln(CL)	20.254	0.00**	Constant+Trend	0.236**	0.099
ln(LC)	16.832	0.00**	Constant+Trend	0.151*	0.071
ln(OH)	44.236	0.00**	Constant+Trend	0.165*	0.062
ln(NE)	15.134	0.00**	Constant+Trend	0.148*	0.106

C. Static Connectedness Network (%)						
	Hospitals (HP)	Clinics (CL)	LTC (LC)	Other HC (OH)	Non-part (NE)	FROM
Hospitals (HP)	2.41	17.19	14.71	35.51	28.18	97.59
Clinics (CL)	15.78	1.93	16.23	41.01	25.06	98.07
LTC facilities (LC)	19.59	15.66	8.76	31.18	24.82	91.24
Other HC Facilities (OH)	26.17	18.37	16.50	10.21	28.75	89.79
Non-participants (NE)	20.13	19.44	20.51	37.82	2.11	97.89
TO	81.66	70.66	67.95	147.52	106.80	474.59
Normalized	16.33	14.13	13.59	29.50	21.36	94.92
NET (NTDCI)	−15.93	−27.41	−23.29	57.72	8.91	TCI=94.92
# of transmitters	1	1	1	4	3	

Notes: The whole sample period spanned from 1997 to 2023, generating a total of 27 annual observations. "*", and "**" represent 5% and 1% significance levels, respectively. The percentage (%) of contribution to the forecast error variance of number of nurses in the sector *i* coming from that in the sector *j* using the TVP-VAR extended-joint connectedness approach. The row titled "Contribution to others" ("Contribution from others") shows the % of contribution of each sector (except the given sector) to (from) all others. The net total directional connectedness index (*NTDCI)* is the difference between "Contribution to others" and "Contribution from others" for each sector. A positive (negative) sign of the *NTDCI* of sector *i* suggests that the number of licensed nurses in sector *i* is a net transmitter (receiver) of nurse employment spillovers. The total number of *NPDCI* transmitters by each sector *i* is reported in the bottom row of Table 1.

connectedness index (*TCI*)—shown in the bottom-right corner of the matrix—is computed as the average of the total spillovers across all sectors (ie, the sum of either the rows or columns divided by five). It is further divided into sector-specific contributions to overall spillovers, as shown in the normalized contributions at the bottom of Panel C. Finally, the net-pairwise directional connectedness index (*NPDCI*) summarizes the bilateral transmission strengths between sectors *i* and *j*, and the number of *NPDCI* transmitters reflects the extent to which a sector exerts greater influence over others in terms of employment spillovers.

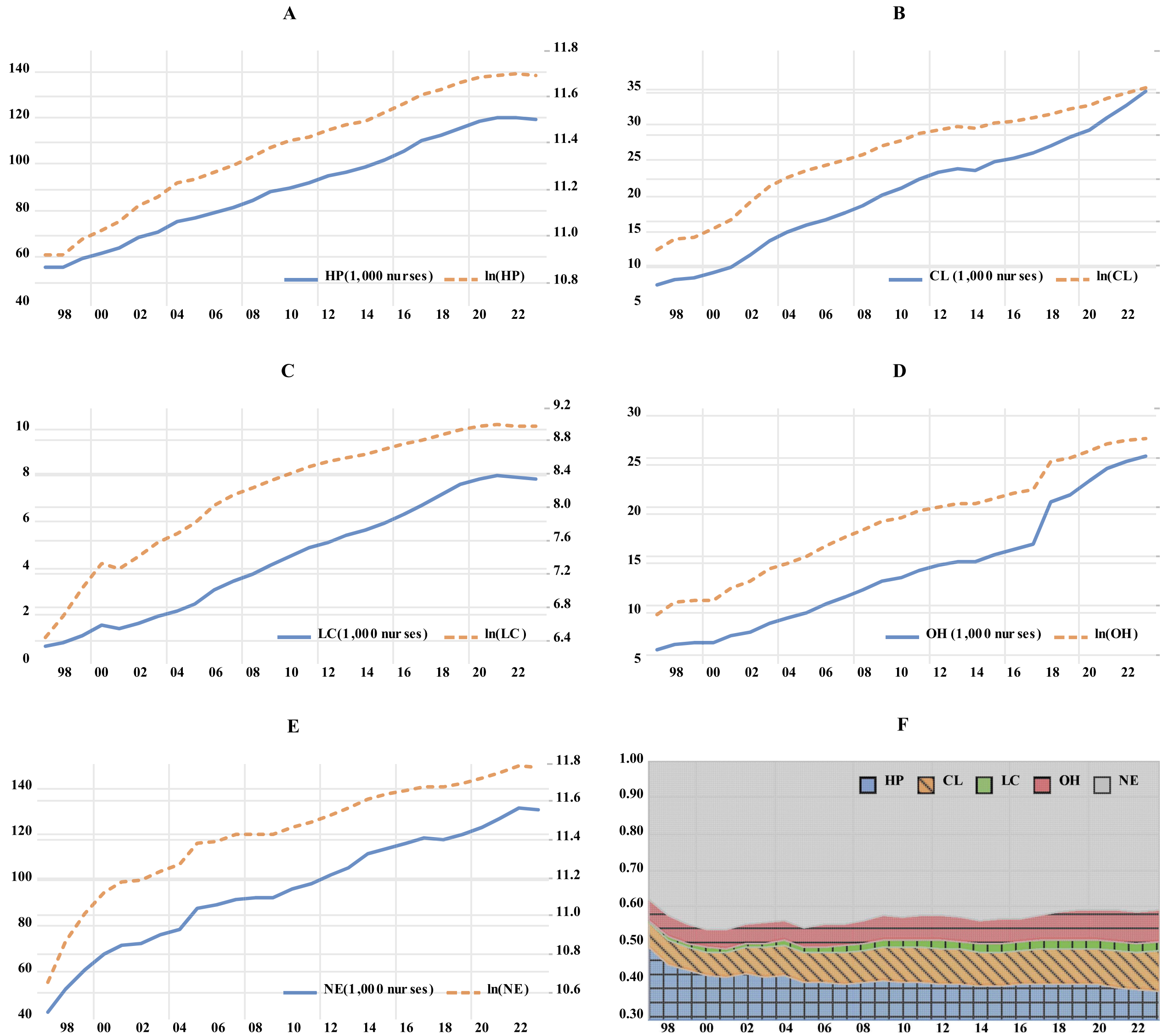

Figure 1 Time series plots for all variables used for the network connectedness analyses.
Notes: Sub-figures (**A–E**) depict total number of licensed nurses employed in hospitals, clinics, long-term care facilities, other healthcare facilities, and non-nursing labor market, respectively. Sub-figure (**F**) presents the distribution of total number of licensed nurses across these sectors.

As shown in Panel C of Table 1, the *TCI* is 94.92%. This indicates that approximately 94.92% of the total forecast error variance in nurse employment across the five sectors can be attributed to spillovers from shocks within the nurse employment behavior network, namely, employment choices across various practice settings such as hospitals, clinics, LTC facilities, other healthcare facilities, and non-nursing roles. Notably, nurse employment in other healthcare facilities and non-participation in the nursing labor market together account for 50.86% of the *TCI*, underscoring their dominant role in driving system-wide employment dynamics. Although nurse employment in other healthcare facilities and non-participation in the nursing labor market (nurse employment in hospitals, clinics, and long-term care facilities) were identified as net transmitters (receivers) of spillovers based on the positive (negative) values of the *NTDCI* (see bottom of Panel C), their potential to act as both transmitters and receivers within the nurse employment behavior network remains evident.

Figures 2A–D illustrate the complete bidirectional relationships between nurse employment in sector *i* and sector *j*. In this figure, HP, CL, LC, and OH denote nurse employment in hospitals, clinics, LTC facilities, and other healthcare facilities, respectively, while NE represents non-participation in the nursing labor market. As shown in Figure 2A, there are ten net pairwise relationships ($=C_2^{10}$) among the five sector-specific nurse employment categories. To add clarity, the complete

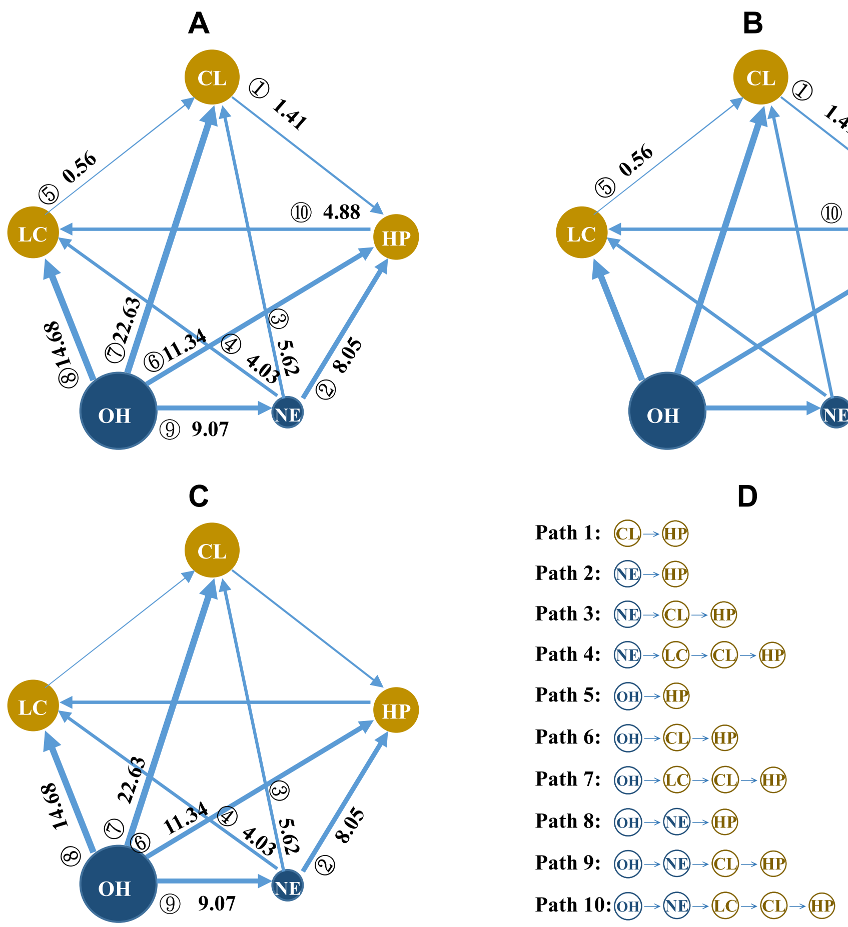

Figure 2 Static connectedness network.

Notes: Sub-figures (**A**–**C**) display the overall static connectedness network, the network of net receivers, and the network of net transmitters, respectively. Sub-figure (**D**) presents the spillover pathways affecting nurse employment in the hospital sector. HP, CL, LC, and OH represent nurse employment in hospitals, clinics, LTC facilities, and other healthcare facilities, respectively, and NE represents non-participation in the nursing labor market. The size of nodes indicates the overall magnitude of transmission/reception of spillovers for each sector. The blue (yellow) color of each node denotes the specific sector is a net transmitter (receiver). The thickness of the arrows reflects the strength of the spillover between a pair of sectors. The thicker arrows show the stronger spillovers between two sectors.

network is further divided into two sub-networks: the network of net receivers (Figure 2B) and the network of net transmitters (Figure 2C). While the magnitude of transmission or reception (node size) may not consistently differ between net transmitters and receivers, the spillover intensity, represented by arrow thickness, is generally stronger among net transmitters compared to net receivers. Given the central role of hospital nurse shortages in shaping inpatient care quality, Figure 2D identifies ten distinct spillover pathways through which nurse employment shocks originating in other sectors transmit to the hospital sector. These pathways elucidate the underlying transmission mechanisms of nurse employment spillovers across various practice settings and highlight their potential influence on staffing dynamics within hospitals.

In summary, the static analysis demonstrates that nurse employment decisions in one sector substantially influence staffing across other sectors. Employment in other healthcare facilities and non-nursing roles is particularly influential, accounting for nearly half of all observed employment dynamics. These findings underscore the importance of workforce planning that considers the broader labor market and cross-sector interactions rather than focusing solely on hospital staffing.

Dynamic Connectedness Network Analysis

Panel A of Table 2 demonstrates that the means of the total connectedness index (*TCI*) and net total directional connectedness indices (*NTDCI*s) are consistent with those reported in Panel C of Table 1. Ten pairs of *NPDCI*s with positive means are used to illustrate dominant nurse employment spillovers from sector *i* to sector *j*. Several indicators shown in Panel B are constructed to capture intersectoral interdependencies in nurse employment over the study period.

Table 2 Descriptive Statistics and Dynamic Connectedness Network

A. Descriptive Statistics for connectedness indices					
Variables	Description	Mean	SD	Min	Max
TCI	Total connectedness index within the nurse employment behavior network	94.918	2.758	90.758	100.000
$NTDCI_{HP}$	Net total directional connectedness index for hospitals	−15.932	19.044	−47.109	48.108
$NTDCI_{CL}$	Net total directional connectedness index for clinics	−27.411	27.442	−69.025	18.169
$NTDCI_{LC}$	Net total directional connectedness index for LTC facilities	−23.294	49.981	−95.117	84.458
$NTDCI_{OH}$	Net total directional connectedness index for other healthcare facilities	57.723	37.784	−24.338	119.477
$NTDCI_{NE}$	Net total directional connectedness index for non-nursing labor market	8.913	23.214	−52.374	47.798
$NPDCI_{CL\rightarrow HP}$	Net pairwise directional connectedness index for nurse employment spillovers from clinics to hospitals.	1.410	6.989	−14.480	20.085
$NPDCI_{NE\rightarrow HP}$	Net-pairwise directional connectedness index for nurse employment spillovers from non-nursing labor market to hospitals	8.054	7.360	−13.233	20.647
$NPDCI_{NE\rightarrow CL}$	Net-pairwise directional connectedness index for nurse employment spillovers from non-nursing labor market to clinics	5.623	10.761	−10.172	27.856
$NPDCI_{NE\rightarrow LC}$	Net-pairwise directional connectedness index for nurse employment spillovers from non-nursing labor market to LTC facilities	4.303	10.695	−14.434	27.304
$NPDCI_{LC\rightarrow CL}$	Net-pairwise directional connectedness index for nurse employment spillovers from LTC facilities to clinics.	0.563	14.376	−15.392	29.877
$NPDCI_{OH\rightarrow HP}$	Net-pairwise directional connectedness index for nurse employment spillovers from other healthcare facilities to hospitals	11.344	9.293	−22.316	18.511
$NPDCI_{OH\rightarrow CL}$	Net-pairwise directional connectedness index for nurse employment spillovers from other healthcare facilities to clinics	22.635	12.019	−2.478	37.250
$NPDCI_{OH\rightarrow LC}$	Net-pairwise directional connectedness index for nurse employment spillovers from other healthcare facilities to LTC facilities	14.678	16.132	−20.438	39.226
$NPDCI_{OH\rightarrow NE}$	Net-pairwise directional connectedness index for nurse employment spillovers from other healthcare facilities to non-nursing labor market.	9.067	10.662	−12.392	39.977
$NPDCI_{HP\rightarrow LC}$	Net-pairwise directional connectedness index for nurse employment spillovers from hospitals to LTC facilities	4.876	11.072	−19.710	18.594
B. Descriptive Statistics for Variables Used Hospital Production and Determinants for Nurse Employment Spillovers					
Variables	Description	Mean	SD	Min	Max
$I(NTDCI_{HP}<0)$	$I(NTDCI_{HP}<0)=1$, if $NTDCI_{HP}<0$; $I(NTDCI_{HP}<0)=0$, if others.	0.885	0.326	0.000	1.000
$I(NTDCI_{CL}<0)$	$I(NTDCI_{CL}<0)=1$, if $NTDCI_{CL}<0$; $I(NTDCI_{CL}<0)=0$, if others.	0.846	0.368	0.000	1.000
$I(NTDCI_{LC}<0)$	$I(NTDCI_{LC}<0)=1$, if $NTDCI_{LC}<0$; $I(NTDCI_{LC}<0)=0$, if others.	0.692	0.471	0.000	1.000
$I(NTDCI_{OH}>0)$	$I(NTDCI_{OH}>0)=1$, if $NTDCI_{OH}>0$; $I(NTDCI_{OH}>0)=0$, if others.	0.846	0.368	0.000	1.000
$I(NTDCI_{NE}>0)$	$I(NTDCI_{NE}>0)=1$, if $NTDCI_{NE}>0$; $I(NTDCI_{NE}>0)=0$, if others.	0.808	0.402	0.000	1.000
$I(NPDCI_{CL\rightarrow HP}>0)$	$I(NPDCI_{CL\rightarrow HP}>0)=1$, if $NPDCI_{CL\rightarrow HP}>0$; $I(NPDCI_{CL\rightarrow HP}>0)=0$, if others.	0.577	0.504	0.000	1.000
$I(NPDCI_{NE\rightarrow HP}>0)$	$I(NPDCI_{NE\rightarrow HP}>0)=1$, if $NPDCI_{NE\rightarrow HP}>0$; $I(NPDCI_{NE\rightarrow HP}>0)=0$, if others.	0.962	0.196	0.000	1.000
$I(NPDCI_{NE\rightarrow CL}>0)$	$I(NPDCI_{NE\rightarrow CL}>0)=1$, if $NPDCI_{NE\rightarrow CL}>0$; $I(NPDCI_{NE\rightarrow CL}>0)=0$, if others.	0.615	0.496	0.000	1.000

(*Continued*)

Table 2 (Continued).

$I(NPDCI_{NE\rightarrow LC}>0)$	$I(NPDCI_{NE\rightarrow LC}>0)=1$, if $NPDCI_{NE\rightarrow LC}>0$; $I(NPDCI_{NE\rightarrow LC}>0)=0$, if others.	0.654	0.485	0.000	1.000
$I(NPDCI_{LC\rightarrow CL}>0)$	$I(NPDCI_{LC\rightarrow CL}>0)=1$, if $NPDCI_{LC\rightarrow CL}>0$; $I(NPDCI_{LC\rightarrow CL}>0)=0$, if others.	0.385	0.496	0.000	1.000
$I(NPDCI_{OH\rightarrow HP}>0)$	$I(NPDCI_{OH\rightarrow HP}>0)=1$, if $NPDCI_{OH\rightarrow HP}>0$; $I(NPDCI_{OH\rightarrow HP}>0)=0$, if others.	0.885	0.326	0.000	1.000
$I(NPDCI_{OH\rightarrow CL}>0)$	$I(NPDCI_{OH\rightarrow CL}>0)=1$, if $NPDCI_{OH\rightarrow CL}>0$; $I(NPDCI_{OH\rightarrow CL}>0)=0$, if others.	0.923	0.272	0.000	1.000
$I(NPDCI_{OH\rightarrow LC}>0)$	$I(NPDCI_{OH\rightarrow LC}>0)=1$, if $NPDCI_{OH\rightarrow LC}>0$; $I(NPDCI_{OH\rightarrow LC}>0)=0$, if others.	0.769	0.430	0.000	1.000
$I(NPDCI_{OH\rightarrow NE}>0)$	$I(NPDCI_{OH\rightarrow NE}>0)=1$, if $NPDCI_{OH\rightarrow NE}>0$; $I(NPDCI_{OH\rightarrow NE}>0)=0$, if others.	0.808	0.402	0.000	1.000
$I(NPDCI_{HP\rightarrow LC}>0)$	$I(NPDCI_{HP\rightarrow LC}>0)=1$, if $NPDCI_{HP\rightarrow LC}>0$; $I(NPDCI_{HP\rightarrow LC}>0)=0$, if others.	0.692	0.471	0.000	1.000
BED	Number of hospital general beds per 10,000 population	41.767	1.113	39.380	43.610
LOS	Average length of stay per admission (days)	9.547	0.483	8.680	10.250
RAD	Readmission within 14 days after discharge (% of total admissions)	8.835	0.447	7.897	9.437
NRS	Regular monthly wage for nurses at the 2021 price level (NT$1000)	42.496	1.706	39.937	47.275
C. KPSS Unit Root Test					
Variables	Tend T-stat	Bootstrap p value	Specification Test	Level	1st Difference
ln(*TCI*)	−0.295	1.00	Constant	0.096	0.107
ln(RAD)	1.852	0.98	Constant	0.174	0.419
ln(BED)	4.467	0.99	Constant	0.401	0.111
ln(LOS)	1.055	0.94	Constant	0.214	0.450

Notes: Since nurse employment spillovers were generated using first-differenced nurse employment data, only 26 annual observations (covering the period from 1998 to 2023) were available for the GETS modeling approach.

For example, the net spillover indicators, $I(NTDCI_j<0)$ and $I(NTDCI_j>0)$, are used to identify whether sector j functions as a net receiver or net transmitter of nurse employment spillovers throughout the research period. Similarly, the pairwise indicator $I(NPDCI_{i\rightarrow j}>0)$ reflects the presence of directional employment spillovers from sector i to sector j. The KPSS tests[45] presented in Panel C generally indicate that all time series are stationary. Time plots for the variables described in Table 2 are displayed in Figures 3–5. A detailed discussion of the descriptive statistics reported in Table 2 is provided in the Supplementary Materials.

In summary, the dynamic analysis shows that nurse employment across sectors is highly interdependent, with certain sectors consistently acting as net transmitters or receivers of workforce changes. Staffing shifts in one area—such as hospitals, clinics, or other healthcare settings—can ripple across the entire nursing labor market. These findings underscore the importance of accounting for broader labor market dynamics in workforce planning to improve nurse retention, optimize staff distribution, and promote more stable staffing.

Employment Spillovers and Inpatient Care Quality

Panel A of Table 3 reports the total connectedness index (*TCI*) and net spillover indicators on inpatient care quality, and Panel B depicts the effects of the dynamic transmission of nurse employment spillovers on the same outcome. Model diagnostic tests for residual normality, the absence of serial correlation, and homoskedasticity suggest that the GETS-selected models provide a statistically appropriate fit for the data (see model specification tests at the bottom of Table 3). Although the GETS modeling approach is particularly well-suited for identifying well-fitting models in small-sample contexts—such as the 26 annual observations used in this study—robustness of the estimates was further ensured through the application of a bootstrap procedure. Specifically, robust standard errors were obtained via 20,000 residual-based bootstrap replications. The resulting distributions of the bootstrapped standard errors appear to be approximately

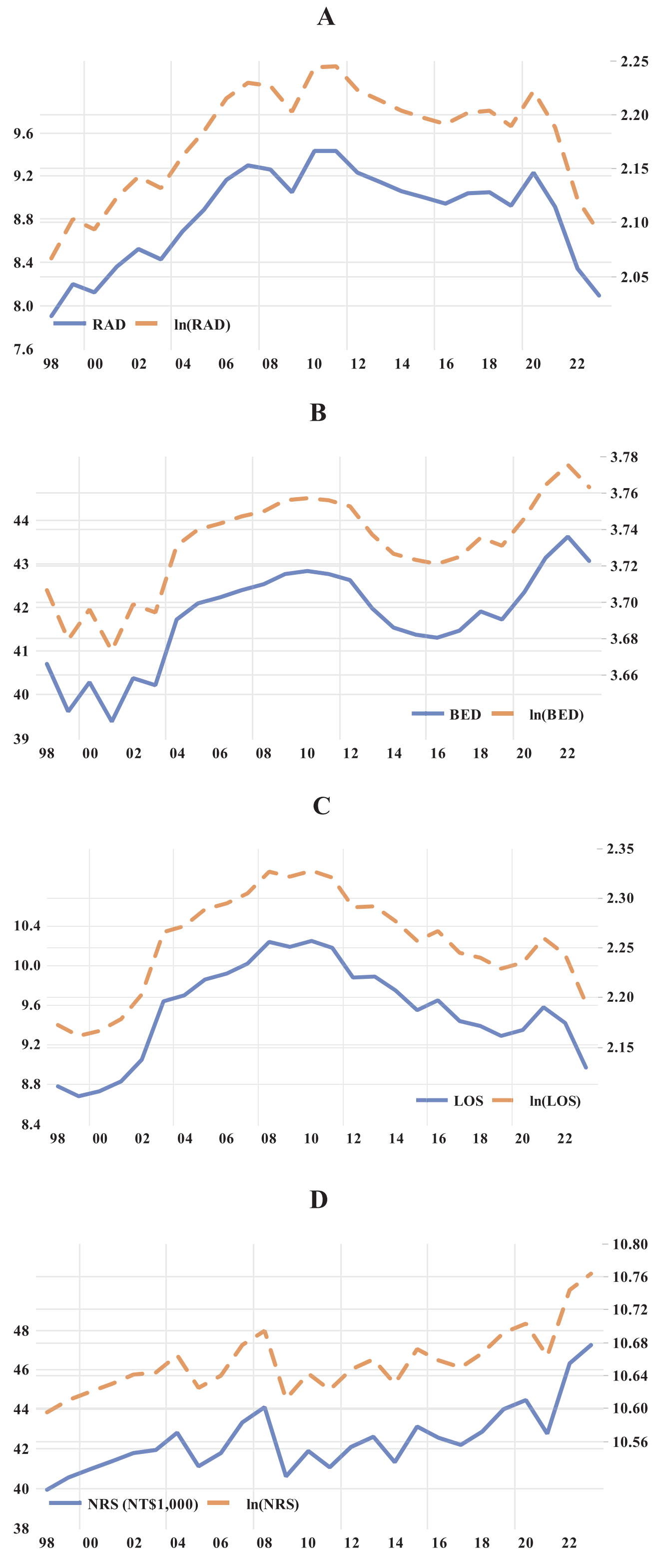

Figure 3 Time series plots of inpatient care quality and control variables used in the GETS modeling approach.

Notes: Sub-figures (**A–D**) show 14-day readmission rate (as a measure of inpatient care quality), the number of hospital general beds per 10,000 population, the average length of stay, and regular monthly wage for nurses, respectively.

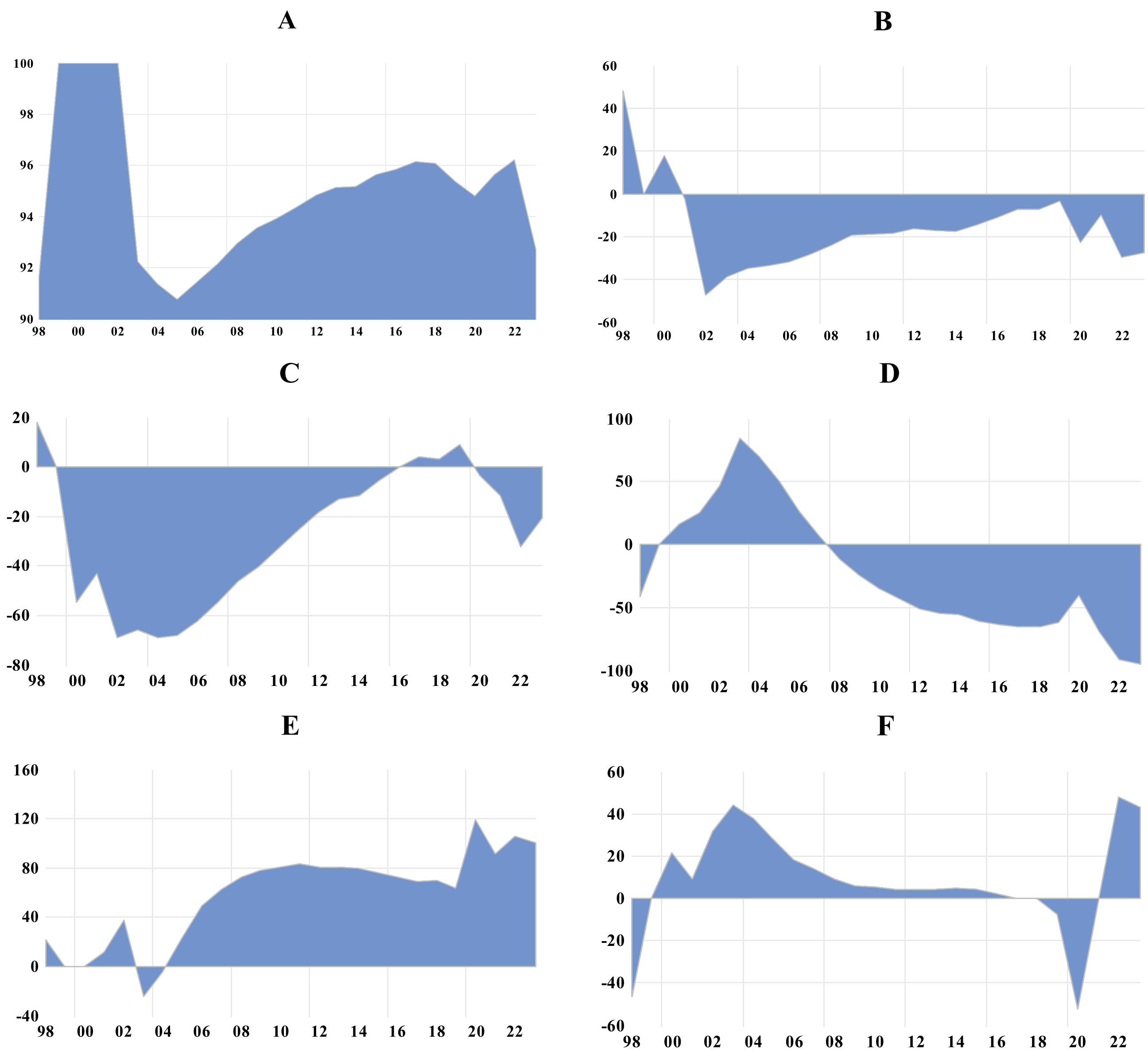

Figure 4 Time series plots of total and net nurse employment spillover effects across sectors.
Notes: Sub-figure (**A**) presents the Total Connectedness Index (*TCI*) within the nurse employment behavior network, and sub-figures (**B**–**F**) display the Net Total Directional Connectedness Indices (*NTDCI*) for hospitals ($NTDCI_{HP}$), clinics ($NTDCI_{CL}$), LTC facilities ($NTDCI_{LC}$), other healthcare facilities ($NTDCI_{OH}$), and non-nursing labor market ($NTDCI_{NE}$), respectively.

symmetric and normally distributed (see Figure S1–S4). Both Panels A and B indicate that the number of general hospital beds has an insignificant effect on inpatient care quality, whereas a longer average length of stay per admission is significantly associated with worse inpatient care quality. Panel A illustrates a negative association between the *TCI* and inpatient care quality and reveals that non-participation in the nurse labor market—when functioning as a net transmitter of employment spillovers—is associated with a lower 14-day readmission rate.

As shown in Panel B, seven out of ten pairwise spillover indicators, $I(NPDCI_{i\to j}>0)$, were retained in the model based on the GETS modeling approach. Among these, five indicators, $I(NPDCI_{CL\to HP}>0)$, $I(NPDCI_{NE\to CL}>0)$, $I(NPDCI_{NE\to LC}>0)$, $I(NPDCI_{LC\to CL}>0)$, and $I(NPDCI_{OH\to HP}>0)$, exhibit negative effects on the 14-day readmission rate. In contrast, the remaining two indicators, $I(NPDCI_{OH\to CL}>0)$ and $I(NPDCI_{OH\to NE}>0)$, demonstrate positive effects. Importantly, the estimated coefficients of these seven indicators enable the evaluation of six out of ten identified pathways of nurse employment spillovers directed toward hospitals (as illustrated in Figure 2D) and their influence on inpatient care quality.

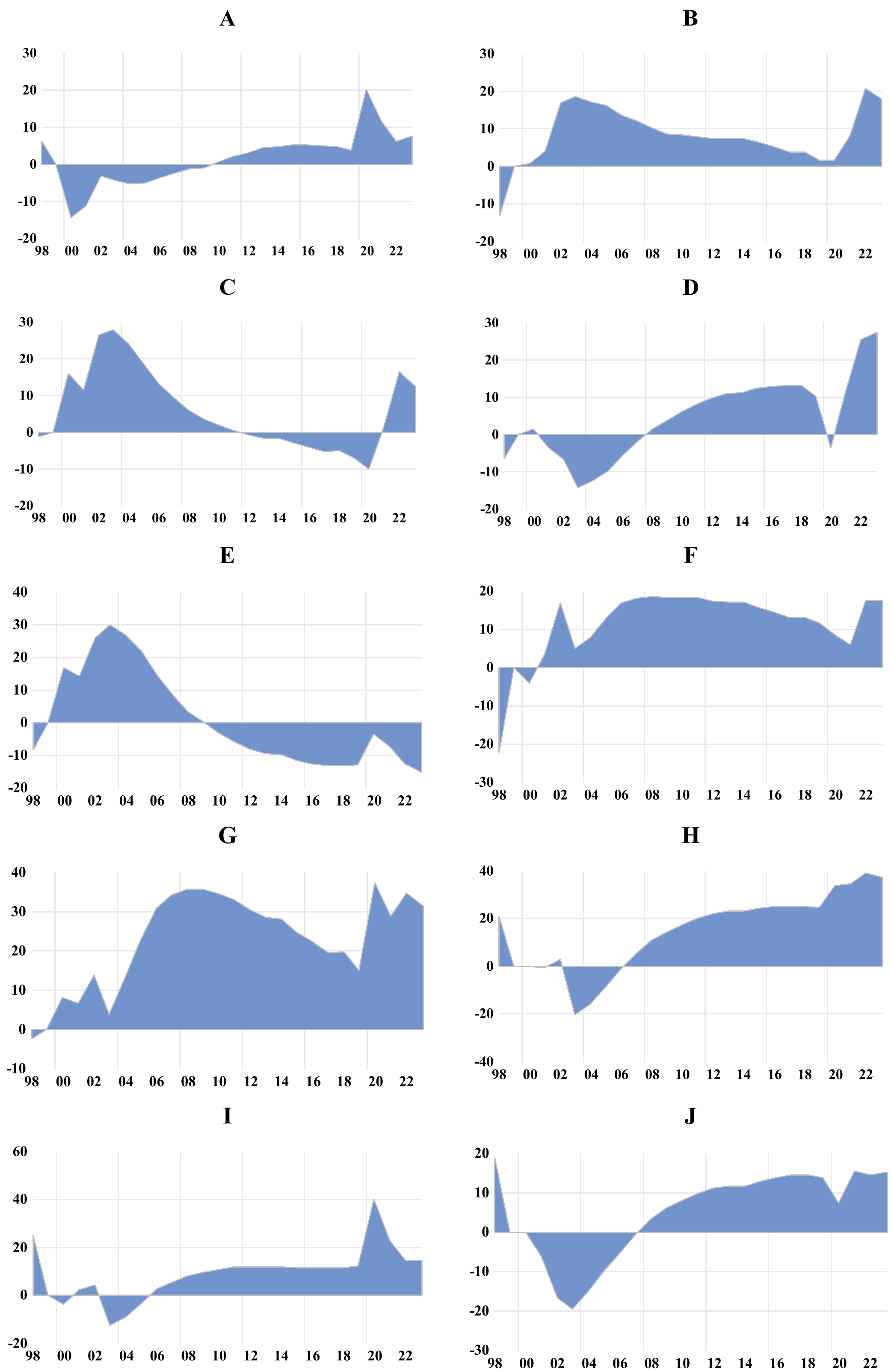

Figure 5 Time series plots of net pairwise nurse employment spillover effects across sectors.

Notes: Sub-figures (**A**–**J**) display the Net Pairwise Directional Connectedness Indices (*NPDCI*) for nurse employment spillovers: (**A**) clinics → hospitals ($NPDCI_{CL\rightarrow HP}$), (**B**) non-nursing labor market → hospitals ($NPDCI_{NE\rightarrow HP}$), (**C**) non-nursing labor market → clinics ($NPDCI_{NE\rightarrow CL}$), (**D**) non-nursing labor market → long-term care facilities ($NPDCI_{NE\rightarrow LC}$), (**E**) long-term care facilities → clinics ($NPDCI_{LC\rightarrow CL}$), (**F**) other healthcare facilities → hospitals ($NPDCI_{OH\rightarrow HP}$), (**G**) other healthcare facilities → clinics ($NPDCI_{OH\rightarrow CL}$), (**H**) other healthcare facilities → LTC facilities ($NPDCI_{OH\rightarrow LC}$), (**I**) other healthcare facilities → non-nursing labor market ($NPDCI_{OH\rightarrow NE}$), and (**J**) hospitals → LTC facilities ($NPDCI_{HP\rightarrow LC}$).

Table 3 Transmission of Nurse Employment Spillovers versus Inpatient Care Quality

Panel A: Net Effects of All Sectors			Panel B: Pairwise Effects from i to j Sector		
Variables	Coeff	T Stat	Variables	Coeff	T Stat
ln(LOS)	1.156	(9.31)**	ln(LOS)	0.983	(10.62)**
ln(BED)	−0.054	(−0.26)	ln(BED)	−0.111	(−0.58)
Constant	−3.241	(−2.60)*	Constant	0.456	(0.75)
ln(*TCI*)	0.668	(3.67)**	I($NPDCI_{CL\rightarrow HP}$>0): I(1) **Path 1:** CL → HP	−0.164	(−5.98)**
I($NTDCI_{NE}$>0)	−0.035	(−3.12)**			
			I($NPDCI_{NE\rightarrow CL}$>0): I(3)	−0.029	(−3.12)**
			I($NPDCI_{NE\rightarrow LC}$>0): I(4)	−0.041	(−4.04)**
			I($NPDCI_{LC\rightarrow CL}$>0): I(5)	−0.186	(−6.40)**
			I($NPDCI_{OH\rightarrow HP}$>0):I(6) **Path 5:** OH → HP	−0.080	(−3.58)**
			I($NPDCI_{OH\rightarrow CL}$>0): I(7)	0.172	(5.90)**
			I($NPDCI_{OH\rightarrow NE}$>0): I(9)	0.049	(4.78)**
			Wald Tests for Spillover Pathways Effects		
			Spillover Pathways	Coeff	(p value)
			I(3)+I(1) **Path 3:** NE → CL → HP	−0.193	(<0.01)**
			I(4)+I(5)+I(1) **Path 4:** NE → LC → CL → HP	−0.391	(<0.01)**
			I(7)+I(1) **Path 6:** OH → CL → HP	0.008	(0.80)
			I(9)+I(4)+I(5)+I(1) **Path 10:** OH → NE → LC → CL → HP	−0.342	(<0.01)**
Specification Tests	Stat	(p value)	Specification Tests	Stat	(p value)
Ho: Normality	0.025	(0.99)	Ho: Normality	0.995	(0.61)
Ho: No Serial Corr	0.705	(0.41)	Ho: No Serial Corr	0.309	(0.59)
Ho: Homoskedasticity	0.293	(0.59)	Ho: Homoskedasticity	0.491	(0.49)
R^2		83.53%	R^2		92.81%
$Adj\text{-}R^2$		80.39%	$Adj\text{-}R^2$		88.76%
GETS excluding Variables		I($NTDCI_{HP}$<0) I($NTDCI_{CL}$<0) I($NTDCI_{LC}$<0) I($NTDCI_{OH}$>0)	GETS excluding Variables		I($NPDCI_{NE\rightarrow HP}$>0) I($NPDCI_{OH\rightarrow LC}$>0) I($NPDCI_{HP\rightarrow LC}$>0)

Notes: "*", and "**" denote significance levels of 5% and 1%, respectively. The general-to-specific modeling approach was employed to select variables for constructing a parsimonious model. Bootstrapped t-statistics were derived from standard errors obtained through 20,000 residual-based bootstrap replications. The blue (yellow) color of each node denotes the specific sector is a net transmitter (receiver).

For example, the effects of spillovers from clinics to hospitals (**Path 1: CL → HP**) and from other healthcare facilities directly to hospitals (**Path 5: OH → HP**) are signified by the coefficients of I($NPDCI_{CL\rightarrow HP}$>0) and I($NPDCI_{OH\rightarrow HP}$>0), respectively. The effects of the remaining four pathways (ie, **Path 3**: **NE → CL → HP, Path 4: NE → LC → CL → HP, Path 6: OH → CL → HP**, and **Path 10: OH → NE → LC → CL → HP**) can be assessed using Wald tests on linear combinations of the relevant coefficient estimates. Our analyses exemplify that all identified pathways of nurse employment spillovers into hospitals are associated with improvements in inpatient care quality, with the exception of Path 6 (**Path 6**: **CL → HP**), which does not exhibit any significant effects. Figures 6A–G plots seven *NPDCI* values corresponding to seven pairwise spillover indicators, I($NPDCI_{i\rightarrow j}$>0), against nurses' regular monthly wages. The OLS-estimated slopes in these plots are positive for $NPDCI_{CL\rightarrow HP}$, $NPDCI_{NE\rightarrow LC}$, $NPDCI_{OH\rightarrow HP}$, and $NPDCI_{OH\rightarrow CL}$, negative for $NPDCI_{LC\rightarrow CL}$, and statistically insignificant for $NPDCI_{NE\rightarrow CL}$ and $NPDCI_{OH\rightarrow NE}$. These findings indicate that wage increases promote nurse employment transitions from clinics (Figure 6A) and other healthcare facilities (Figure 6E) to hospitals, as well as from other healthcare facilities (Figure 6F) and non-participation (Figure 6C) to clinics. Conversely, wage increases are not effective in incentivizing spillovers from non-participation (Figure 6B) or LTC facilities (Figure 6D) to clinics or from other healthcare facilities to non-participation (Figure 6G).

In summary, nurse inflows from other sectors into hospitals are associated with lower readmission rates, emphasizing the value of coordinated staffing across the healthcare system. Importantly, higher wages can encourage nurses to transition from clinics and other healthcare facilities to hospitals, enhancing workforce stability where it is most needed. These findings suggest that policies supporting nurse retention, cross-sector mobility, and targeted wage incentives can strengthen the nursing workforce and improve hospital care quality, providing practical guidance for healthcare planners and policymakers.

Sensitivity Analysis

The inclusion of the 2020–2021 COVID-19 outbreak years may have disproportionately influenced employment spillover dynamics and inpatient readmission rates, given the unprecedented shifts in healthcare demand and workforce policies during this period. It is important to note that the TVP-VAR extended joint connectedness approach cannot be estimated using

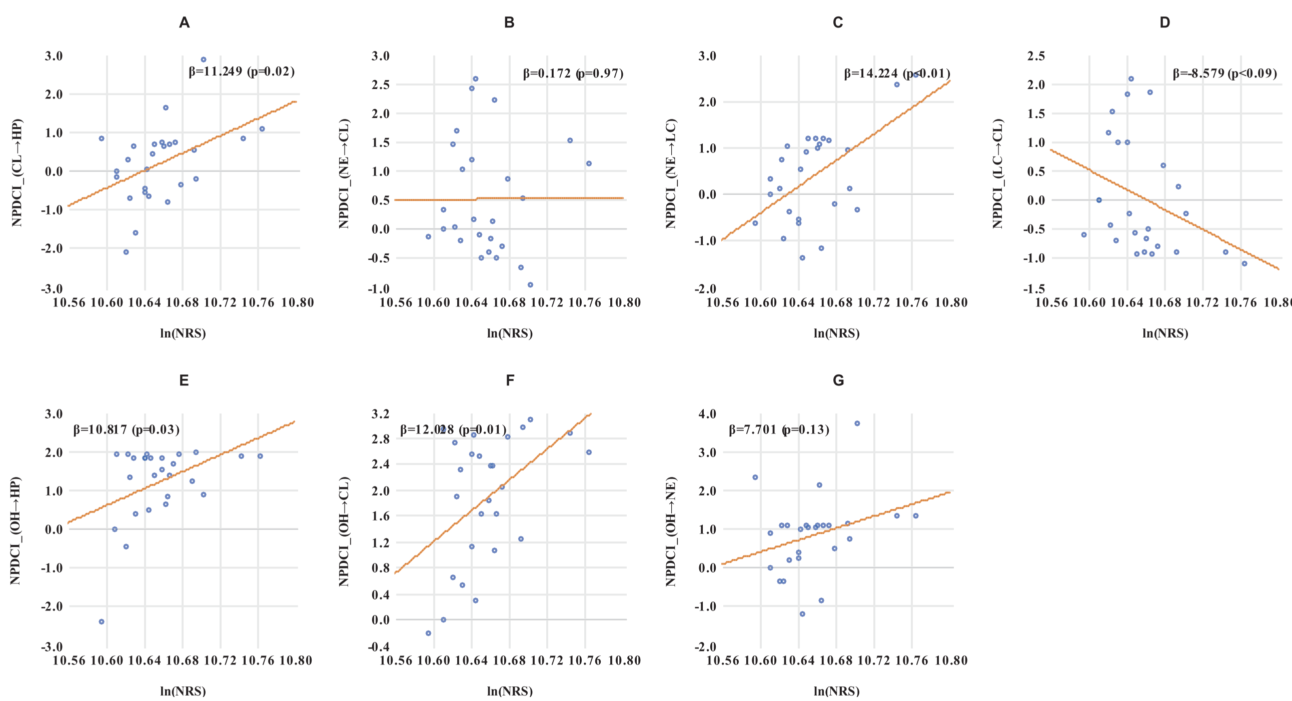

Figure 6 Scatter plots for nurse employment spillovers dynamics against nurse wage.

Notes: Sub-figures (**A**–**G**) demonstrate the Net Pairwise Directional Connectedness Indices (*NPDCI*) for nurse employment spillovers across sectors relative to regular monthly wage for nurses (NRS): (**A**) $NPDCI_{CL\rightarrow HP}$,(**B**) $NPDCI_{NE\rightarrow CL}$,(**C**) $NPDCI_{NE\rightarrow LC}$,(**D**) $NPDCI_{LC\rightarrow CL}$,(**E**) $NPDCI_{OH\rightarrow HP}$,(**F**) $NPDCI_{OH\rightarrow CL}$,and (**G**) $NPDCI_{OH\rightarrow NE}$.

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discontinuous time-series data. Nevertheless, the time-varying nature of this approach enables it to accommodate structural shifts in the data-generating process (eg, those induced by the COVID-19 pandemic), making it particularly well-suited for analyzing evolving nurse employment spillovers. To mitigate potential distortions attributable to the pandemic, we re-estimated the GETS models after excluding data from 2020 to 2021. The results, presented in Table 4, indicate that the goodness-of-fit tests and the signs and significance of the estimated coefficients remain consistent with those in Table 3. Moreover, the R^2 and adjusted R^2 values in Table 4 are slightly higher, reinforcing the robustness of the GETS modeling approach.

Table 4 Sensitivity Analysis for Transmission of Nurse Employment Spillovers versus Inpatient Care Quality

Panel A: Net Effects of All Sectors			Panel B: Pairwise Effects from i to j Sector		
Variables	Coeff	T Stat	Variables	Coeff	T Stat
ln(LOS)	1.169	(10.24)**	ln(LOS)	0.998	(10.89)**
ln(BED)	−0.044	(−0.21)	ln(BED)	−0.182	(−0.90)
Constant	−3.442	(−2.78)*	Constant	0.682	(1.05)
ln(*TCI*)	0.696	(4.00)**	I($NPDCI_{CL\rightarrow HP}$>0): I(1) **Path 1:** OH → HP	−0.157	(−4.89)**
I($NTDCI_{NE}$>0)	−0.031	(−2.46)*			
			I($NPDCI_{NE\rightarrow CL}$>0): I(3)	−0.031	(−3.10)**
			I($NPDCI_{NE\rightarrow LC}$>0): I(4)	−0.035	(−2.59)*
			I($NPDCI_{LC\rightarrow CL}$>0): I(5)	−0.172	(−4.87)**
			I($NPDCI_{OH\rightarrow HP}$>0):I(6) **Path 5:** NE → CL → HP	−0.074	(−3.03)**
			I($\mathrm{NPDCI}_{OH\rightarrow CL}$>0): I(7)	0.160	(4.64)**
			I($\mathrm{NPDCI}_{OH\rightarrow NE}$>0): I(9)	0.048	(4.62)**
			Wald Tests for Spillover Pathways Effects		
			Spillover Pathways	Coeff	(p value)
			I(3)+I(1) **Path 3:** NE → LC → CL → HP	−0.188	(<0.01)**
			I(4)+I(5)+I(1) **Path 4:** OH → CL → HP	−0.365	(<0.01)**
			I(7)+I(1) **Path 6:** OH → NE → LC → CL → HP	0.008	(0.80)
			I(9)+I(4)+I(5)+I(1) **Path 10:** OH → CL → HP	−0.341	(<0.01)**
Specification Tests	Stat	(p value)	Specification Tests	Stat	(p value)
Ho: Normality	0.600	(0.74)	Ho: Normality	0.808	(0.67)
Ho: No Serial Corr	0.691	(0.42)	Ho: No Serial Corr	0.656	(0.43)

(*Continued*)

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Table 4 (Continued).

Ho: Homoskedasticity	0.949	(0.34)	Ho: Homoskedasticity	0.013	(0.91)
R^2		86.76%	R^2		93.42%
$Adj\text{-}R^2$		83.98%	$Adj\text{-}R^2$		89.19%

Notes: The data exclude the years 2020–2021 to avoid distortions associated with the COVID-19 pandemic. "*", and "**" denote significance levels of 5% and 1%, respectively. The general-to-specific modeling approach was employed to select variables for constructing a parsimonious model. Bootstrapped t-statistics were derived from standard errors obtained through 20,000 residual-based bootstrap replications. The blue (yellow) color of each node denotes the specific sector is a net transmitter (receiver).

Discussion

This study aims to quantify evolving interrelationships and employment spillovers within the nurse employment network using the TVP-VAR extended joint connectedness approach, examine their association with inpatient care quality via the GETS modeling approach, and assess the impact of changes in nurses' wages on these spillover effects. The results corresponding to these research aims are presented below:

Policy Implications of Employment Spillover Dynamics

Shocks to nurse employment across the five sector-specific practice settings account for approximately 95% of the total forecast error variance in nurse employment (see total connectedness index, *TCI* in Tables 1–2). This merits the use of dynamic connectedness network analysis for revealing the transmission of nurse employment spillovers. Several policy implications emerge from these empirical findings and are discussed below.

First, nurse employment in hospitals, clinics, and LTC facilities functions as a net receiver of employment shocks, whereas nurse employment in other healthcare facilities and the non-nursing labor market serves as a net transmitter (see Tables 1–2). These patterns align with the ongoing nursing workforce crisis in Taiwan, where it is projected that clinical settings will face a shortage of 55,000 to 74,000 nurses by 2030.[21] Significantly, the overall magnitude of spillover transmission from other healthcare facilities is 6.48 times (=57.723÷8.913) greater than that from the non-nursing labor market. This suggests that policy interventions that target nurse outflows from other healthcare facilities into hospitals, clinics, and LTC facilities may be more effective than those focused on drawing nurses back from non-nursing roles. Nevertheless, the overall capacity to receive spillovers, ie, the magnitude of reception, is highest for clinics, followed by LTC facilities, and lowest for hospitals. Therefore, even if policies successfully trigger nurse outflows from transmitting sectors, the highest relative inflow of nurses is expected in clinics, followed by LTC facilities, and lowest in hospitals. If policies aim to increase hospital nurse employment by redirecting nurses from other healthcare facilities and non-nursing roles, then policymakers must consider the limited absorption capacity of hospitals, as identified in Tables 1–2. This highlights the potential limit to policy effectiveness, as nurse employment spillovers may be partially absorbed by other receiving sectors.

Second, evidence in Panel A of Table 3 suggests that total intersectoral interdependencies in nurse employment (measured by the *TCI*) within the nurse employment behavior network are negatively associated with inpatient care quality. In contrast, drawing nurses back from non-nursing roles shows a positive association with inpatient care quality. These patterns may reflect underlying structural inefficiencies in the healthcare system, as evidenced by reports indicating that over 40% of Taiwanese nurses are unwilling to enter or remain in the profession[17] and by the "great resignation" in nursing observed in the United States during the COVID-19 pandemic.[46,47] Third, the analysis identified ten distinct spillover pathways through which nurse employment shocks originating in other sectors transmit to hospitals (see Figure 2D). These pathways expand the conceptualization of hospital nurse employment from a static, sector-specific measure, as used in previous studies,[4–15] toward a system-wide, dynamically interconnected framework that reflects the broader structure of nurse employment across the healthcare system. Among these ten pathways, six originate in other healthcare facilities, three in the non-nursing labor market, and one in clinics (Figure 2D). Upon assessing the link between the transmission of employment spillovers and inpatient care quality (Panel B of Table 3), four of the six pathways from other healthcare facilities, along with the pathway from the non-nursing labor market to hospitals, were either excluded or found to be statistically insignificant under the GETS modeling approach. These findings warrant a more cautious interpretation of the presumed importance of other healthcare facilities as primary sources of employment shocks affecting hospital staffing. Fourth, we found that nurse inflows from non-nursing sectors into nursing roles enhanced inpatient care quality (see Panel B of Table 3). Five spillover pathways—from clinics, other healthcare facilities, and non-nursing sectors into hospitals—were positively associated with patient outcomes. These findings align with extensive international evidence showing that inadequate nurse staffing and shortages are linked to poorer inpatient outcomes across North America,[4,6,10] Europe,[2–4,7–9] Asia,[6,12,14,15] and the Southern Hemisphere.[4,5] Collectively, these results underscore the importance of policies that facilitate nurse re-entry and cross-sector mobility to strengthen hospital staffing and improve care quality.

Role of Wage on Spillover Pathways

The findings reported in Panel B of Table 3 reinforce the positive impact of nurse employment spillovers transmitted from clinics, the non-nursing labor market and other healthcare facilities to hospitals on inpatient care quality. This includes **Path 1: CL → HP**, **Path 3**: **NP → CL → HP**, **Path 4: NP → LC → CL → HP**, **Path 5: OH → HP**, and **Path 10:** OH → NP → LC → CL → HP. These results are consistent with a substantial body of the literature demonstrating the beneficial impact of nurse staffing on inpatient outcomes.[4–15] Furthermore, inadequate compensation for evening and mid-night shift work is a critical factor underlying the shortage of hospital nurses, particularly for positions requiring around-the-clock patient care.[48] Scatter plots of the net-pairwise directional connectedness indices (*NPDCIs*) against nurses' wages suggest that wage increases facilitate nurse employment spillover transitions from clinics (Figure 6A) and other healthcare facilities (Figure 6E) to hospitals, as well as from other healthcare facilities (Figure 6F) and non-participation (Figure 6C) to clinics. These findings align with evidence from the United States, where higher wages have been shown to reduce job dissatisfaction and turnover intentions among nurses.[49] They also correspond with international patterns, as sustained inflows of recruited nurses into OECD countries are frequently attributed to wage differentials as a key pull factor.[50,51] Importantly, our results provide empirical support for Taiwan's recent strategic intervention, implemented in September 2023, which offers additional compensation to hospitals that improve patient-to-nurse ratios and to nurses working evening and night shifts.[18]

COVID-19 Pandemic Impacts

In response to the COVID-19 pandemic, the Taiwanese government implemented multiple public health interventions—including widespread mask use, social distancing measures, school closures, quarantines, and stay-at-home campaigns—that substantially reduced population mobility.[52,53] Consequently, Figures 3A–D illustrate a downward trend in 14-day readmission rates and length of stay, alongside an upward trend in hospital general bed availability, as well as a sharp break in nurse regular wages. Although the pandemic may have disproportionately influenced employment spillover dynamics and inpatient readmission rates, the results of our sensitivity analysis suggest that the findings are robust. This robustness likely reflects Taiwan's successful containment of COVID-19 without resorting to stringent lockdowns,[53] combined with the advantages of the GETS modeling approach, which leverages automation and machine learning to minimize subjective bias.[23]

Study Limitations and Directions for Future Research

It is imperative to acknowledge several research limitations to ensure a comprehensive understanding of this study. First, this study utilizes consistent and long-term time-series data for the analyses; however, data on non-participation in nursing labor market and nurses' wages were unavailable for certain periods. To address these gaps, backward forecasting methods were applied to estimate values for the earlier years. While such an approach is common in long-term time-series analyses, it introduces a degree of estimation uncertainty and should be recognized as a limitation of this study. Second, as the nurse employment data used in this study are aggregated time-series data, the analysis is subject to the risk of ecological fallacy.[54] Consequently, the empirical results cannot be interpreted as reflecting individual nurses' decisions regarding their choice of practice setting. Third, the identification of nurse employment spillover transmission in this study is based on a data-driven approach—specifically, the GETS modeling method[23]—rather than a theory-driven framework. We recommend that future research develop a dynamic hospital production theory that can simultaneously account for the transmission of nurse employment spillovers across sectors and their impact on inpatient care quality.

Conclusion

This study advances the conceptualization of nurse workforce dynamics by moving beyond static, sector-specific measures toward a dynamic, system-wide framework that captures the evolving interrelationships and spillovers across healthcare sectors. By integrating the TVP-VAR extended joint connectedness approach with the GETS modeling framework, we demonstrate that staffing shifts in one sector—whether hospitals, clinics, LTC facilities, or non-nursing roles—can reverberate throughout the broader nursing labor market and meaningfully affect inpatient care quality. The findings underscore the importance of coordinated workforce policies, including wage adjustments and cross-sector mobility, to optimize nurse distribution and enhance patient outcomes. Taiwan's experience offers unique international insights: its single-payer system and abundant administrative data allow for precise mapping of employment spillovers, providing a model for other countries to assess and manage nurse workforce dynamics in a data-driven manner. These results highlight the potential for dynamic, network-based analyses to inform policy interventions aimed at sustaining healthcare system resilience and quality of care worldwide.

Data Sharing Statement

Data will be made available on request to Wen-Yi Chen.

Ethics

We used secondary data that does not require taking consent. No human participants or biological specimens were involved. The data collection process was approved by the Research Ethics Committee of Taichung Tzu Chi Hospital with the Certificate of Exempt Review ID: REC113-28.

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Disclosure

The authors report no conflicts of interest in this work.

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