Risk Management and Healthcare Policy

Dovepress
open access to scientific and medical research

Open Access Full Text Article

ORIGINAL RESEARCH

On the Association Between Demographic Structural Change and the Effectiveness of Nurse Staffing Policy for Inpatient Care: Evidence from Taiwan

Yi-Ling Lai[1,2], Wen-Yi Chen[3,*], Shiuan-Shinn Lee[1,*], Yung-Po Liaw[1,4,5]

[1]Department of Public Health and Institute of Public Health, Chung Shan Medical University, Taichung, 402367, Taiwan; [2]Community Health Center, Taichung Tzu Chi Hospital, Buddhist Tzu Chi Medical Foundation, Taichung, 427213, Taiwan; [3]Department of Senior Citizen Service Management, National Taichung University of Science and Technology, Taichung, 403301, Taiwan; [4]Department of Medical Imaging, Chung Shan Medical University Hospital, Taichung, 402367, Taiwan; [5]Institute of Medicine, Chung Shan Medical University, Taichung, 402367, Taiwan

*These authors contributed equally to this work

Correspondence: Wen-Yi Chen, Department of Senior Citizen Service Management, National Taichung University of Science and Technology, 193 Sec 1, San-Min Road, Taichung, 403301, Taiwan, Tel +886 4 22196932, Email chenwen@nutc.edu.tw; Shiuan-Shinn Lee, Department of Public Health, Chung Shan Medical University, 110, Section 1, Jianguo North Road, Taichung, 402367, Taiwan, Tel +886 4 24730022 Ext 12185, Email shinn@csmu.edu.tw

Purpose: This study investigates the influence of demographic changes on the effectiveness of hospital nurse staffing policy, measured by the cumulative response of inpatient care quality to adjustments in hospital nurse staffing levels in Taiwan.

Methods: The research design utilized in this study aligns with the observational time-series methodology, and a total of 99 monthly time-series observations were collected from multiple databases administered by the Taiwan government over the period from January 2015 to March 2023. Specifically, the time-varying parameter vector autoregressive and autoregressive distributed lag models were employed to investigate the association between age distribution and nurse staffing policy effectiveness.

Results: The time-varying impulse responses of the unplanned 14-day readmission rate after discharge to changes in nurse staffing levels indicate a positive association between patient-to-nurse ratios and unplanned 14-day readmission rates across various types of hospitals. Nevertheless, the effectiveness of hospitals' nurse staffing policy is observed to diminish with population aging, particularly evident in medical centers and regional hospitals.

Conclusion: Policymakers should establish lower mandated patient-to-nurse ratios, grounded in practical nurse workforce planning, to address the needs of an aging society and enhance inpatient care quality through improved nurse staffing in hospitals.

Keywords: demographic structural change, nurse staffing, inpatient care quality, time-varying parameter vector autoregressive model, autoregressive distributed lags model

Introduction

Background

In accordance with the Global Nursing Workforce and International Migration Report published by the International Council of Nurses in 2022, titled "Sustain and Retain in 2022 and Beyond", the global nursing workforce is facing a shortage of approximately 13 million professionals due to the increased demand for healthcare services resulting from the COVID-19 pandemic.[1] In fact, the shortage of nursing personnel on a global scale is not a unique phenomenon solely attributed to the COVID-19 pandemic.[2] The insufficiency of nursing staff represents a pervasive challenge evident in diverse healthcare systems, including the National Health Service system (eg, the United Kingdom,[3] Ireland,[4] and the Nordic countries[5]), the social health insurance system (eg, Germany,[6] Canada,[7] Japan,[8] and Taiwan[9]), the private health insurance system (eg, the United States[10]), and other contexts.[11] The deficit in nursing staff not only compounds the challenges within the nursing profession's working conditions but also exerts a detrimental influence on patient outcomes (or healthcare quality),[12] and hospital financial performance.[13] Prior research on nursing staffing shortages can be

Received: 10 March 2024
Accepted: 14 June 2024
Published: 25 June 2024

delineated into two primary themes. The first theme focuses on the physiological and psychological responses exhibited by nursing personnel in response to the deterioration of working conditions within the nursing practice, encompassing aspects such as burnout,[14,15] depression,[15] job satisfaction,[14] intention to leave and turnover,[5,12,14,16] and occupational injury risks.[14,17] The second theme underscores the impact of nurse staffing shortages on various dimensions of care quality, including inpatient care quality,[12,18–20] emergency care quality,[21] ICU care quality,[22] and long-term care quality.[23,24] In order to enhance the nursing practice environment, mitigate nursing personnel shortages, and consequently ensure the sustained elevation of healthcare quality, most countries globally have instituted substantial regulations and controls governing nurse staffing levels within hospital settings.

According to a study conducted by Aiken et al, the average patient-to-nurse ratio (*PNR*, hereafter) was found to vary from approximately 3.4 to 17.9 patients per nurse across countries belonging to the Organization for Economic Cooperation and Development.[25] Norway and Ireland exhibited the most favorable *PNR*s, with averages falling below seven patients per nurse. In close succession were the Netherlands, Sweden, and Switzerland, with *PNRs* ranging from seven to eight patients per nurse. The United Kingdom reported an average *PNR* of nearly 9, whereas Belgium and Spain demonstrated *PNR*s exceeding 10 patients per nurse, suggesting a comparatively higher care burden on nursing personnel. Moreover, recent studies suggest that the average *PNRs* in some advanced Asian countries are approximately 7.5 in South Korea, 10.5 in Japan, and 8.1 in Taiwan.[26,27] The identified positive correlation between nurse staffing levels and care quality, as highlighted in the study by Aiken et al[25] and many other studies,[12,18–25,27] underscores the potential of regulating hospital nurse staffing as a crucial policy instrument in healthcare administration. This instrument has the capacity to serve as an effective means of monitoring and upholding inpatient care quality to elevated standards. Consequently, recent studies examining the effectiveness of nurse staffing policy have predominantly concentrated on the effect of changes in nurse staffing on inpatient care quality. The methodologies employed in these investigations frequently utilize intervention models within a natural experiment framework. For instance, de Cordova et al utilized interrupted time-series analysis to scrutinize the effects of reporting and disclosure measures on *PNRs* in the United States, and their findings indicated a noteworthy reduction in *PNR* subsequent to the implementation of reporting and disclosure measures, signifying an amelioration in the care burden on nursing personnel.[28] Similarly, Van et al employed the same methodology to evaluate the impact of intervention measures on *PNRs* in the United States, revealing a positive influence of diminished *PNRs* on inpatient care quality.[20] This positive correlation between nurse staffing levels and inpatient care quality is also evident in numerous other nursing studies.[12,18–20,22,25,27]

Demographic Change & Nurse Staffing

Notwithstanding the established positive influence of nurse staffing levels on inpatient care quality, the accelerated aging of the global population presents a substantial challenge to the effectiveness of hospitals' nurse staffing policy from two distinct perspectives. First, the increasing elderly population amplifies the demand for healthcare, exacerbating the severity of nurse shortages.[29] Second, the rise in unmarried or childless individuals contributes to a departure from familial care responsibilities,[30] leading to fewer economically active people financing health and welfare systems, while the demands on these systems continue to increase.[31,32] Hence, comprehending the potential impact of demographic structural changes on the effectiveness of hospitals' nurse staffing policy emerges as a crucial concern within the realms of healthcare services. Previous studies on the influence of demographic structural changes on policy effectiveness have primarily included empirical studies within diverse economic markets, encompassing the monetary market,[33,34] securities market,[35] exchange market[36] real estate market,[37] and various commodity markets.[37] Nevertheless, research examining the nexus between demographic changes and the effectiveness of healthcare policies is scarce within the literature on healthcare services. To the best of the authors' knowledge, Lin et al conducted the initial study to scrutinize the impact of demographic changes on the effectiveness of the outpatient copayment policy in Taiwan, and their findings suggested that the effectiveness of the outpatient copayment policy would be enhanced by the aging population.[38] In contrast to Lin et al results, Chen et al undertook a study on the influence of demographic structural changes on the effectiveness of emergency department copayment policies in Taiwan.[39] Their results indicated that if the policy objective is to curtail the overall utilization of emergency services in medical centers, adjustments to copayment levels necessitated by an aging society would need to be significantly higher than the presently established standards.[39]

Purposes of the Study

In order to fill the research gap pertaining to the impact of demographic changes on nurse staffing policy effectiveness, this study endeavored to investigate the relationship between demographic changes and hospital nurse staffing policy effectiveness. Taiwan was specifically selected as the study region for three primary reasons: First, Taiwan stands as one of the most rapidly aging countries worldwide. The proportion of the elderly population (aged 65 and above) in Taiwan surged from 7% in 1993 to 14% in 2018, with projections anticipating a further increase to 20% by 2025.[40] This transition from an aging society (7%) to an aged society (14%) occurred within a mere 25 years, and the subsequent shift from an aged society (14%) to a super-aged society (20%) is anticipated to transpire within a span of just 7 years, underscoring significant demographic changes.[40] Second, while Taiwan's National Health Insurance (NHI, hereafter) program provides comprehensive healthcare services, including inpatient, outpatient, and dental services, traditional Chinese medicine, and prescription drugs, the implementation of a global budgeting payment scheme aimed at controlling the rapid growth of healthcare expenditure may potentially restrict the allocation of nursing staff in hospitals.[27,38,39] Third, despite regulatory efforts such as mandated minimum *PNRs* and the use of the *PNR* as a critical indicator for hospital accreditation,[41] the nursing labor market in Taiwan is confronting a significant challenge, with approximately 40% of nurses expressing reluctance to enter the workforce.[42] These circumstances collectively provide a compelling backdrop for the examination of the impact of demographic changes on hospitals' nurse staffing policy.

In this study, we proceed with our investigation on the nexus between demographic changes and the effectiveness of hospitals' nurse staffing policy in the following steps: First, we employ the time-varying parameter vector autoregressive (TVP-VAR, hereafter) model, as proposed by Nakajima,[43] coupled with time-varying impulse-response analyses (TV-IRA, hereafter). This methodology allows us to simulate the impact of nurse staffing adjustments, specifically, the changes in *PNRs*, on inpatient care quality, as measured by the unplanned 14-day readmission rate after discharge (hereafter 14-day readmission rate). The cumulative response of the 14-day readmission rate to changes in *PNR* over a 12-month timespan serves as a metric for assessing the effectiveness of hospitals' nurse staffing policy. This approach addresses a notable gap in the literature by examining the long-run impacts of nurse staffing on inpatient care quality.[20,28,38,39] Second, we employ the autoregressive distributed lags (ARDL, hereafter) model, as introduced by Pesaran et al,[44] to examine the long-run relationship among hospital nurse staffing policy effectiveness and age distribution.

Contribution of the Study

This study makes significant contributions to the literature on the effects of demographic changes on the effectiveness of hospitals' nurse staffing policy based on two aspects: First, differing from prior research on the effectiveness of nurse staffing policies, which frequently concentrates on analyzing the association between nurse staffing levels and inpatient care quality or the short-run effects of nurse staffing policy changes based on one-shock interventions,[20,28] this study introduces a novel approach by utilizing the TVP-VAR model in conjunction with the ARDL model. This innovative methodology enables the analysis of the impact of demographic changes on the effectiveness of hospitals' nurse staffing policy in Taiwan. Second, in contrast to previous studies that relied on a single demographic indicator (such as the proportion of the elderly population, dependency ratio, or economic dependency ratio) to explore the association between demographic changes and policy effectiveness,[34] this study conducts empirical analyses based on the age distribution of the entire population. The results of this study have the potential to serve as crucial references for the Taiwan government in formulating more comprehensive nurse staffing policies aimed at sustaining inpatient care quality within Taiwan's NHI system.

Materials and Methods

Research Design

The primary objective of this study was to investigate the relationship between demographic structural changes and the effectiveness of hospital nurse staffing policy. Demographic structural change refers to significant alterations in the composition of a population over time. To measure the effectiveness of hospital nurse staffing policies, we analyzed the impulse responses of inpatient care quality to changes in nurse staffing over a 12-month period. Therefore, the research design utilized in this study aligns with the observational time-series methodology, and several time-series models were used to analyze secondary data to investigate the primary objective of this study.

Data Collection and Samples

The data utilized for this research were sourced from multiple databases: the Open Database of Taiwan's National Health Insurance (managed by the National Health Insurance Administrative), the Healthcare Quality Database of the Center of Quality Management (under the administration of the Joint Commission of Taiwan), and the Macroeconomics Statistics Database (administered by the Directorate General of Budget, Accounting, and Statistics). Specifically, data pertaining to inpatient care quality (quantified by 14-day readmission rates),[27,45,46] labor input (measured through *PNR* denoting the average number of patients cared for by one nurse per shift),[27] and length of stay per admission (utilized to control for the severity of illnesses)[47] were collected for medical centers, regional hospitals, and district hospitals. These data were employed in the estimation of the hospital production function outlined in the data analysis section below. Subsequently, the effectiveness of hospitals' nurse staffing policy, indicated by the cumulative response of the 14-day readmission rate to a standard deviation change in the *PNR* in acute care wards within a 12-month timespan, was derived from the estimated hospital production function. Additionally, demographic data encompassing the distribution of the population across seven age-specific groups (ie, under 15, aged 15–24, aged 25–34, aged 35–44, aged 45–54, aged 55–64, and 65 or over), healthcare workers' incomes (measured by the real wage level in the healthcare industry[27]), reimbursement payment per diem (utilized to control for hospital competition under Taiwan's NHI global budgeting payment scheme[27]), and business cycles (indicated by the leading indicator of business cycles[48]) were collected. These data were employed to investigate the long-run effects of demographic change on the effectiveness of hospitals' nurse staffing policy. Monthly data spanning from January 2015 to March 2023 were collected, resulting in a total of 99 monthly observations for our analyses. The determination of the observed study period relied upon the availability of the longest and consistently maintained time-series data accessible to academic researchers.

Data Analysis

The empirical procedure used to investigate the association between demographic structural change and the effectiveness of hospitals' nurse staffing policy included two steps: First, we conducted the TV-IRA based on Nakajima's method[43] to obtain the responses of inpatient care quality to changes in nursing staffing within a 12-month timespan across our study period. The magnitude of these impulse responses served as a measure for the effectiveness of hospitals' nurse staffing policy. The methodology utilized in this study to assess policy effectiveness has been extensively employed in prior policy evaluation studies, spanning analyses of monetary and fiscal policies,[33] copayment policies for outpatient care services,[38] and emergency department visits.[39] Second, given that previous studies, including those by Lin et al[38] and Chen et al,[39] have delved into the impact of demographic change on healthcare policy effectiveness, we utilized the ARDL model proposed by Pesaran et al[44] along with Fair and Dominguez's method[49] to delineate the nonlinear relationship between age distribution and the effectiveness of nurse staffing policy. The lag selection procedures and diagnostic assessments of the goodness-of-fit for the ARDL model drew upon methodologies established in prior studies, such as those conducted by Chang and Chen[50] and Chen and Lin.[51] For the sake of brevity, we omit the technical details of the specification and estimation process for the TPV-VAR and ARDL models. Interested readers are referred to the Supplementary Materials of this study for further information. The tabulated description of these two empirical models is presented in Table 1.

Ethical Considerations

This study uses secondary data, specifically monthly economic indicators, aggregate healthcare utilization, and demographic data for all residents in Taiwan. These data did not involve any human participants or tissue, and the data collection process was approved by the Research Ethics Committee of Taichung Tzu Chi Hospital with the Certificate of Exempt Review ID: REC110-23.

Table 1 Tabulated Description for Empirical Models

A. TPV-VAR Model		
Procedures	Description	Variables/Results
Step 1: Model Specification	• Setup the hospital production function for three types of hospitals (ie, medical centers, regional hospitals, district hospitals).	• Output variable: Inpatient care quality (14-day readmission rate) • Input variable: Patient-to-nurse ratio (*PNR*) • Control variable: Length of stay per admission
Step 2: Model Specification Tests	• The break-point unit root test proposed by Perron[52] is used to test for the stationarity of the time series. • The parameter stability test proposed by Hansen[53] is used to test for H_0: TIP-VAR (Time-invariant parameter) model versus H_1: TVP-VAR model.	• ADF statistics and *p* values are generated by Perron's method.[52] • *Sup-F* statistics and *p* values are generated by Hansen's method.[53] • Fisher χ^2 method is used to obtain an aggregate *Sup-F* statistic.[54]
Step 3: Estimation Process	• The Bayesian Markov chain Monte Carlo method, with 10,000 repetitions, is used to simulate responses of the 14-day readmission rate to a standard deviation change in the *PNR* in acute care wards over a 12-month period.[43]	• Effectiveness of nurse staffing policy is indicated by the cumulative response of the 14-day readmission rate to a standard deviation change in the *PNR* ratio in acute care wards within a 12-month timespan
B. ARDL Model		
Procedures	Description	Variables/Results
Step 1: Model Specification	• Setup the linear relationship between age distribution and nurse staffing policy effectiveness for three types of hospitals (ie, medical centers, regional hospitals, district hospitals).	• Dependent variable: The effectiveness of nurse staffing policy • Explanatory variables: Shares of total population at seven specific age groups • Control variables: Hospital competition, income and business cycles
Step 2: Model Re-specification	• Due to incorporate proportions of the population from all age groups, a perfect collinearity issue that prevented the estimation of the linear regression model. • The nonlinear specification based on Fair and Dominquez's method[49] is used to deal with the perfect collinearity.	• Fair and Dominquez's method[49] was utilized to perform the linear and quadratic transformation of age distribution. • The delta method to compute the standard errors of shares of population, facilitating the establishment of 95% confidence intervals for the estimated coefficients.
Step 3: Model Specification Tests	• The break-point unit root test proposed by Perron[52] is used to test for the stationarity of the time series.	• ADF statistics and *p* values are generated by Perron's method.[52] • Mixed orders of time series are found (ie, I(1) or I(0)).
Step 4: Estimation Process	• ARDL model selection procedure introduced by Pesaran and his colleagues[44] was used to generate the modified F-statistics. • The recommended bound testing procedure is used to test for $H_{0:}$ No cointegration (ie, No long-run relationship). • Estimated coefficients of the share of total population at each specific age groups are retrieved by Fair and Dominquez's method.[49]	• The modified F-statistics is denoted as Fpss. • Two pivotal bounds, the upper (I(1)) and lower (I(0)) bounds, are obtained from Pesaran et al[44] • Reject H_0: No cointegration (ie, No long-run relationship), if Fpss >I(1) bound. • The goodness-of-fit for the residuals is evaluated through testing for residual auto-correlation, heteroskedasticity, and normality. • The adjustment parameter, with a significantly negative value, indicates the stability in the dynamic healthcare system.

Results

Panel A of Table 2 provides descriptive statistics for all variables used in estimating the TVP-VAR model. As depicted in Panel A, the average 14-day readmission rates were approximately 1.276%, 1.704%, and 1.427% in medical centers,

Table 2 Descriptive Statistics and Parameter Stability Tests for the TVP-VAR Model

A. Descriptive Statistics

Variables	Description	Mean	SD	Min	Max
RAD^{MC}	Unplanned readmission rate within 14 days after discharge at medical centers (%)	1.276	0.213	0.710	1.730
RAD^{RH}	Unplanned readmission rate within 14 days after discharge at regional hospitals (%)	1.704	0.173	1.230	2.080
RAD^{DH}	Unplanned readmission rate within 14 days after discharge at district hospitals (%)	1.427	0.369	0.720	2.860
PNR^{MC}	Average Patient-to-nurse ratio at acute care wards of medical centers	7.508	0.418	5.943	8.314
PNR^{RH}	Average Patient-to-nurse ratio at acute care wards of regional hospitals	9.217	0.388	7.649	10.007
PNR^{DH}	Average Patient-to-nurse ratio at acute care wards of district hospitals	7.400	0.273	6.649	7.880
LOS^{MC}	Average length of stay per admission at medical centers	8.653	0.294	8.020	9.280
LOS^{RH}	Average length of stay per admission at regional hospitals	9.264	0.320	8.570	9.980
LOS^{DH}	Average length of stay per admission at district hospitals	14.011	0.955	12.010	15.380
SRAD^{MC}	RAD^{MC} ÷ standard deviation of RAD^{MC}	6.000	1.000	3.340	8.138
SRAD^{RH}	RAD^{RH} ÷ standard deviation of RAD^{RH}	9.846	1.000	7.105	12.016
SRAD^{DH}	RAD^{DH} ÷ standard deviation of RAD^{DH}	3.863	1.000	1.950	7.744
SPNR^{MC}	PNR^{MC} ÷ standard deviation of PNR^{MC}	17.962	1.000	14.218	19.889
SPNR^{RH}	PNR^{RH} ÷ standard deviation of PNR^{RH}	23.784	1.000	19.739	25.823
SPNR^{DH}	PNR^{DH} ÷ standard deviation of PNR^{DH}	27.061	1.000	24.315	28.816
SLOS^{MC}	LOS^{MC} ÷ standard deviation of LOS^{MC}	29.467	1.000	27.310	31.600
SLOS^{RH}	LOS^{RH}÷ standard deviation of LOS^{RH}	28.909	1.000	26.745	31.145
SLOS^{DH}	LOS^{DH} ÷ standard deviation of LOS^{DH}	14.673	1.000	12.577	16.106

B. Break-Point Unit Root Test

Variables	De-mean	Break	De-trend	Break	Variables	De-mean	Break	De-trend	Break
SRAD^{MC}	−4.500***	2021M02	−5.989***	2021M03	SPNR^{DH}	−4.322***	2016M02	−5.349***	2021M03
SRAD^{RH}	−3.483*	2016M12	−4.655**	2020M08	SLOS^{MC}	−11.180***	2020M06	−11.181***	2021M01
SRAD^{DH}	−4.675***	2016M10	−4.702**	2020M10	SLOS^{RH}	−5.660***	2018M12	−7.470***	2019M08
SPNR^{MC}	−3.244*	2022M02	−5.076***	2021M03	SLOS^{DH}	−4.660***	2018M12	−5.798***	2017M08
SPNR^{RH}	−3.551**	2021M01	−6.389***	2021M01					

C. Parameter Stability Tests for VAR System

Stability Tests	Medical Centers			Regional Hospitals			District Hospitals		
	SRAD^{MC}	SPNR^{MC}	SLOS^{MC}	SRAD^{RH}	SPNR^{RH}	SLOS^{RH}	SRAD^{DH}	SPNR^{DH}	SLOS^{DH}
Sup-F	8.285***	6.952***	3.993*	2.415	6.613***	13.984***	3.930*	3.788*	9.730***
p value	<0.01	<0.01	0.06	0.41	<0.01	<0.01	0.06	0.07	<0.01

(*Continued*)

Table 2 (Continued).

Fisher χ^2	41.834***	58.705***	36.706***
	10% Critical Value	5% Critical Value	1% Critical Value
CV	11.796	13.687	17.832

Notes: The whole sample period spanned from January 2015 to March 2023, generating a total of 99 monthly observations. Lags were selected by 10% significance level for the break-point unit root tests. TVP-VAR model was estimated by Bayesian Markov Chain Monte Carlo method with 10,000 repetitions, and one lag was selected by the Schwarz Information Criterion. The *p* values for the *Sup-F* were calculated based on Hansen' method.[53] Fisher $\chi 2$ statistics were computed by the Fisher method and the critical values were generated by adjusted the mean false discovery rate.[54]*,**and *** represent 10%, 5% and 1% significance levels, respectively.

regional hospitals, and district hospitals, respectively. The mean *PNR* (ie, the average number of patients cared for by one nurse per shift) was approximately 7.508, 9.217, and 7.400 in medical centers, regional hospitals, and district hospitals, respectively. These results show that, on average, the number of patients that a nurse cares for during a shift varies within the range of 7.400 to 9.217. The length of stay per admission was 8.653, 9.264, and 14.011 days in medical centers, regional hospitals, and district hospitals, respectively. To ensure the comparability of our TV-IRA across different types of hospitals, standardized data were used to estimate the TVP-VAR model. Panel B of Table 2 presents the results of the break-point unit root test.[52] As illustrated in Panel B, regardless of the chosen de-mean or de-trend specification, the null hypotheses of unit root time series were rejected, confirming the stationarity of the time series for all variables used in estimating the TVP-VAR model. The parameter stability tests, assessing the null hypothesis of a time-invariant parameter vector autoregressive model (hereafter, TIP-VAR) against the TVP-VAR model, are outlined in Panel C of Table 2. The *Sup-F* statistics proposed by Hansen[53] yield p-values below the 10% significance level in eight out of nine equations within the three vector autoregressive systems for medical centers, regional hospitals, and district hospitals. Employing the Fisher χ^2 method to obtain an aggregate *Sup-F* statistic[54] for the entire vector autoregressive system in medical centers, regional hospitals, and district hospitals resulted in values of 41.834, 58.705, and 36.706, respectively. These generated χ^2 values surpass the 1% critical value. Consequently, the null hypothesis of parameter stability in the vector autoregressive system was robustly rejected, validating the use of the TVP-VAR model for evaluating the responses of 14-day readmission rates to changes in nurse staffing levels in acute wards across various types of hospitals. The time plots illustrating all variables described in Table 2 are presented in Figure S1 in the Supplementary.

The propagation mechanisms illustrating the impact of nurse staffing on inpatient care quality over the time scales of 1–12 months during our study period for medical centers, regional hospitals, and district hospitals are depicted in Figures 1A–C, respectively. As evident in these figures, the cumulative impulse responses of 14-day readmission rates to an increase in the *PNR* from the 3-month to 12-month time scales were consistently positive for all types of hospitals. These results suggest that a higher burden on nurses caring for patients is associated with poorer inpatient care quality, indicated by higher 14-day readmission rates. Given that Taiwan's hospital nurse staffing policy aims to reduce *PNRs* to enhance inpatient care quality, the observed propagation mechanisms simulate the effectiveness of hospitals' nurse staffing policy over different time scales. Specifically, they indicate the potential positive impact on inpatient care quality if a lower *PNR* was imposed at all time scales during our study period. It is crucial to note that the impact of the nurse staffing policy is most pronounced in regional hospitals, followed by medical centers, and is least significant in district hospitals, particularly at time scales of 6 months and above during our study period. In addition, the gaps in the response of inpatient care quality to a change in *PNR* reduced with increasing time scales, specifically from 3 months to 6 months, from 6 months to 9 months, and from 9 months to 12 months for all types of hospitals. These findings suggest that the effectiveness of hospitals' nurse staffing policy diminishes over time. Furthermore, notable downward trends in the responses of inpatient care quality to a change in *PNR* were observed in medical centers and district hospitals. In contrast, the responses of inpatient care quality to a change in *PNR* in regional hospitals remained relatively stable throughout the study period from January 2015 to March 2023.

Panel A of Table 3 provides descriptive statistics for all variables used in estimating the ARDL model. As illustrated in Panel A, the means of the cumulative response of the 14-day readmission rate to a standardized deviation change in *PNR* in acute care wards within a 12-month timespan are 0.321, 0.626, and 0.288 for medical centers, regional hospitals,

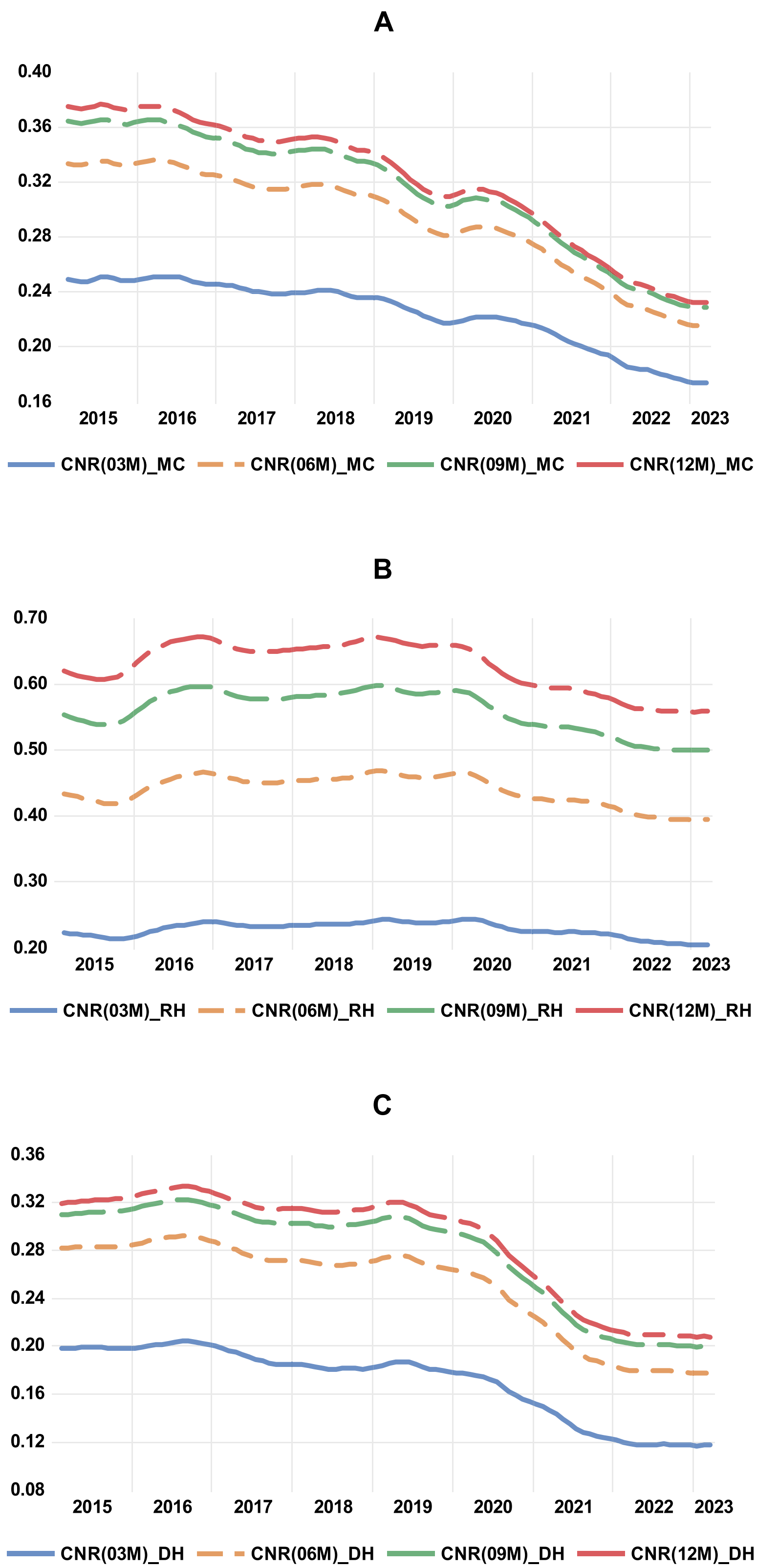

Figure 1 Time plots for the cumulative response of the 14-day readmission rate to a standard deviation change in the patient-to-nurse ratio at acute care wards within a 12-month timespan.

Notes: Sub-figures (**A**–**C**) illustrate the cumulative response of the 14-day readmission rate to a standard deviation change in the patient-to-nurse ratio at acute care wards within a 12-month timespan for medical centers, regional hospitals and district hospitals, respectively.

Table 3 Descriptive Statistics and Co-Integration Tests for ARDL Model

A. Descriptive Statistics

Variables	Descriptive	Mean	SD	Min	Max
CNR^{MC}	Cumulative response of medical center 14-day readmission rate to a standardized unit change of patient-to-nurse ratio at acute care wards within a 12-month period.	0.321	0.046	0.232	0.376
CNR^{RH}	Cumulative response of regional hospital 14-day readmission rate to a standardized unit change of patient-to-nurse ratio at acute care wards within a 12-month period.	0.626	0.038	0.558	0.671
CNR^{DH}	Cumulative response of district hospital 14-day readmission rate to a standardized unit change of patient-to-nurse ratio at acute care wards within a 12-month period.	0.288	0.045	0.208	0.333
Age 1	The share of total population in children group (age <15) (%)	0.145	0.005	0.137	0.156
Age 2	The share of total population aged 15–24 years old (%).	0.116	0.009	0.098	0.128
Age 3	The share of total population aged 25–34 years old (%).	0.135	0.005	0.130	0.147
Age 4	The share of total population aged 35–44 years old (%).	0.161	0.003	0.154	0.164
Age 5	The share of total population aged 45–54 years old (%).	0.153	0.002	0.149	0.157
Age 6	The share of total population aged 55–64 years old (%).	0.143	0.004	0.134	0.149
Age 7	The share of total population in the elderly group (age ≥65) (%)	0.146	0.017	0.120	0.176
z1	Linear transformation of age distribution	−4.521	0.360	−5.140	−3.913
z2	Quadratic transformation of age distribution	−17.714	1.825	−20.811	−14.616
ICE^{MC}	Inpatient care expenditure per diem at medical centers (Constant at 2011 price level, NT$)	11,286.70	864.48	9911.75	12,955.31
ICE^{RH}	Inpatient care expenditure per diem at regional hospitals (Constant at 2011 price level, NT$)	7,171.47	489.65	6405.33	8361.46
ICE^{DH}	Inpatient care expenditure per diem at district hospitals (Constant at 2011 price level, NT$)	4,075.67	358.60	3574.35	4904.48
INC	Average monthly regular earnings of healthcare sector (Constant at 2011 price level, NT$)	56,557.25	1,078.34	53,905.85	58,739.11
CLI	Composite leading indicator index used to measure business cycles	84.087	9.364	71.550	99.840

B. Break-Point Unit Root Test

Variables	De-mean	De-mean	De-trend	De-trend	Variables	De-mean	De-mean	De-trend	De-trend
	Level	1st Diff	Level	1st Diff		Level	1st Diff	Level	1st Diff
CNR^{MC}	−2.420	−3.314*	−5.561***	−4.387**	$\ln(ICE^{MC})$	−3.801**	−13.356***	−5.648***	−8.246***
Break	2019M02	2022M02	2020M01	2020M07	Break	2020M12	2015M11	2019M12	2019M11
CNR^{RH}	−3.730**	−3.758**	−6.828***	−5.257***	$\ln(ICE^{RH})$	−4.985***	−10.926***	−4.330***	−10.573***
Break	2016M01	2016M02	2020M02	2016M02	Break	2018M03	2021M10	2018M03	2017M07
CNR^{DH}	−3.501**	−2.147	−4.738**	−3.410*	$\ln(ICE^{DH})$	−4.376***	−4.878***	−6.671***	−11.237***
Break	2020M07	2019M02	2020M04	2020M03	Break	2022M02	2015M10	2021M02	2017M06

(*Continued*)

Table 3 (Continued).

z1	−3.860**	−7.376***	−4.181**	−7.704***	ln(INC)	−3.987**	−9.737***	−4.753***	−6.987***
Break	2020M04	2019M07	2022M05	2022M02	Break	2018M11	2015M10	2018M06	2019M12
z2	−4.457***	−6.647***	−5.146***	−6.710***	ln(CLI)	−2.760	−4.694***	−5.890***	−7.273***
Break	2022M04	2018M07	2021M09	2022M02	Break	2022M05	2020M10	2020M08	2020M04

C. ARDL Cointegration Tests

Model Specification	ARDL	F_{PSS}	SC (p value)	HET (p value)	BJ (p value)	Sign Levels	I(0)	I(1)
$CNR^{MC} \mid z1,z2,\ln(ICE^{MC}),\ln(INC),\ln(CLI)$	(5,0,0,0,0,0)	4.788***	0.938 (0.40)	1.249 (0.27)	0.319 (0.85)	10%	2.080	3.000
$CNR^{RH} \mid z1,z2,\ln(ICE^{RH}),\ln(INC),\ln(CLI)$	(4,0,0,1,1,2)	4.901***	1.363 (0.26)	0.836 (0.62)	1.987 (0.37)	5%	2.390	3.380
$CNR^{DH} \mid z1,z2,\ln(ICE^{DH}),\ln(INC),\ln(CLI)$	(3,0,1,0,1,0)	3.668**	0.215 (0.81)	1.502 (0.15)	3.313 (0.19)	1%	3.060	4.150

Notes: Lags were selected by the Hannan-Quinn criterion (HQ) to estimate the ARDL models with maximal 6 lags, and constant was included in the cointegrating equation. SC, HET, and BJ denote testing statistics for tests of residuals correlation, heteroskedasticity, and normality, respectively. F_{PSS} denotes the *F* statistics testing the null hypothesis of no cointegrating relationship. *,**and *** represent 10%, 5% and 1% significance levels, respectively. I(0) and I(1) are the stationary and non-stationary bounds, respectively.

and district hospitals, respectively. These results indicate that, on average, a reduction of 0.321, 0.626, and 0.288 standard deviations in the 14-day readmission rate over a 12-month period for medical centers, regional hospitals, and district hospitals, respectively, can be anticipated with a corresponding reduction of one standard deviation in the *PNR*. The average shares of the population across seven age-specific groups during our observed period ranged from 11.6% (aged 15–24) to 16.1% (aged 35–44). The means of linear and quadratic transformations of age distribution were −4.521 and −17.714, respectively. Real inpatient care reimbursement payments per diem were approximately NTD 11,287, NTD 7,171, and NTD 4,076 for medical centers, regional hospitals, and district hospitals, respectively. The average real monthly regular earnings in the healthcare industry are around NTD 56,557, and the mean score of the composite leading indicator index is 84.087. The time plots illustrating all variables except for the effectiveness of hospitals' nurse staffing policy described above are presented in Figure S2 in the Supplementary.

Panel B of Table 3 presents the results of the break-point unit root test. As illustrated, the cumulative response of the 14-day readmission rate to a standard deviation change in *PNR* at district hospitals and the composite leading indicator index is identified as a non-stationary (stationary) series when the de-mean (de-trend) specification is used to generate the testing statistics. Nevertheless, the first difference in these time series is found to be stationary, regardless of the chosen de-mean or de-trend specification for generating testing statistics, suggesting that these variables belong to the first-order stationary (I (1)) time series. Furthermore, irrespective of the chosen de-mean or de-trend specification, the null hypotheses of unit root time series are rejected for real inpatient care reimbursement payments per diem at all types of hospitals, linear and quadratic transformations of age distribution, average real monthly regular earnings in the healthcare industry, and the cumulative response of the 14-day readmission rate to a standard deviation change in *PNR* at medical centers and regional hospitals. Similar results rejecting the null hypothesis of the unit root were obtained when testing the differences in these time series for the unit root property. This confirmation suggests that these time series exhibit level stationary characteristics (I(1)). Hence, some of the variables employed for estimating the ARDL model exhibit level stationary characteristics (I(0)), while others fall into the first-order difference stationary category (I(1)). It is worth noting that the ARDL cointegration methodology can accommodate both I(0) and I(1) time series to test for long-run (ie, cointegrating) relationships.[44] Consequently, we proceed with our cointegration analyses under the ARDL model.

Panel C of Table 3 indicates that our ARDL specifications satisfy the assumptions of goodness-of-fit, including independence, homogeneity, and normality in the residuals. Additionally, the upper and lower bounds of critical values for the cointegration relationship were derived from Pesaran et al[44] by setting the number of explanatory variables to six . As indicated in Panel C of Table 2, the F_{PSS} statistics used to test the null hypothesis of no cointegration against cointegrating (ie, long-run) relationships among inpatient care reimbursement payments per diem, linear and quadratic transformations of age distribution, average real monthly regular earnings in the healthcare industry, the composite leading indicator index, and the cumulative response of the 14-day readmission rate to a standard deviation change in the *PNR* at medical centers, regional hospitals, and district hospitals are 4.788, 4.901, and 3.668, respectively. These values exceed the upper bounds of critical values at the 5% (or more rigorous) significance level, strongly confirming the presence of cointegrating (ie, long-run) relationships among the examined time series.

Table 4 reports the ARDL estimates along with the respective estimated long-run coefficients and the effects of demographic changes on the effectiveness of hospitals' nurse staffing policy (measured by the cumulative response of the 14-day readmission rate to a standard deviation change in *PNR*) retrieved using Fair and Dominguez's methods.[49] As illustrated in Table 4, the

Table 4 Effects of Demographical Transitions on Effectiveness of Nurse Staffing Policy

Medical Centers			**Regional Hospitals**			**District Hospitals**		
Variables	Coeff	T value	Variables	Coeff	T value	Variables	Coeff	T value
CNR^{MC}_{t-1}	−0.017	−3.34***	CNR^{RH}_{t-1}	−0.019	−4.88***	CNR^{DH}_{t-1}	−0.014	−4.18***
z_{1t}	0.130	3.51***	z_{1t}	0.148	2.59**	z_{1t}	0.047	1.35
z_{2t}	−0.026	−3.50***	z_{2t}	−0.029	−2.57**	z_{2t}	−0.009	−1.33
$\ln(ICE^{MC})_t$	−0.003	−1.30	$\ln(ICE^{RH})_{t-1}$	−0.012	−3.02***	$\ln(ICE)_t$	−0.006	−2.67***
$\ln(INC)_t$	−0.003	−1.11	$\ln(INC)_{t-1}$	−0.007	−1.52	$\ln(INC)_{t-1}$	−0.001	−0.21
$\ln(CLI)_t$	−0.005	−2.71***	$\ln(CLI)_{t-1}$	−0.008	−2.36**	$\ln(CLI)_t$	−0.004	−1.64
Constant	0.219	3.86***	Constant	0.392	3.68***	Constant	0.130	2.48**
ΔCNR^{MC}_{t-1}	1.826	17.77***	ΔCNR^{RH}_{t-1}	1.521	14.01***	ΔCNR^{DH}_{t-1}	1.309	14.58***
ΔCNR^{MC}_{t-2}	−1.514	−7.56***	ΔCNR^{RH}_{t-2}	−0.853	−4.80***	ΔCNR^{DH}_{t-2}	−0.403	−4.26***
ΔCNR^{MC}_{t-3}	0.765	3.85***	ΔCNR^{RH}_{t-3}	0.219	2.13**	Δz_{2t}	−0.001	−0.14
ΔCNR^{MC}_{t-4}	−0.192	−1.97*	$\Delta\ln(ICE^{RH})_t$	−0.005	−1.68*	$\Delta\ln(ICE^{RH})_t$	0.011	2.00**
			$\Delta\ln(INC)_t$	0.015	2.25**			
			$\Delta\ln(CLI)_t$	−0.112	−3.21***			
			$\Delta\ln(CLI)_{t-1}$	0.106	3.01***			
R^2	95.39%		R^2	97.57%		R^2	96.00%	
Adj-R^2	95.18%		Adj-R^2	97.18%		Adj-R^2	95.52%	
Long-run Coefficients								
Variables	Coeff	T value	Variables	Coeff	T value	Variables	Coeff	T value
z_{1t}	7.731	3.76***	z_{1t}	7.641	3.28***	z_{1t}	3.293	1.49
z_{2t}	−1.524	−3.81***	z_{2t}	−1.479	−3.24***	z_{2t}	−0.638	−1.46
$\ln(ICE)_t$	−0.164	−1.43	$\ln(ICE)_t$	−0.628	−3.68***	$\ln(ICE)_t$	−0.398	−2.96***

(*Continued*)

Table 4 (Continued).

Medical Centers			**Regional Hospitals**			**District Hospitals**		
$\ln(INC)_t$	−0.176	−1.03	$\ln(INC)_t$	−0.365	−1.50	$\ln(INC)_t$	−0.051	−0.21
$\ln(CLI)_t$	−0.293	−2.00**	$\ln(CLI)_t$	−0.389	−2.61**	$\ln(CLI)_t$	−0.305	−1.80*
Constant	13.023	3.52***	Constant	20.254	5.10***	Constant	9.057	2.72***
Error Correction Coefficients								
	Coeff	T value		Coeff	T value		Coeff	T value
Adjusted Coeff	−0.017	−6.00***		−0.019	−6.07***		−0.014	−5.25***
Age Distribution Coefficients								
Age	Coeff	T value	Age	Coeff	T value	Age	Coeff	T value
Age 1 (<15)	5.759	3.99***	Age 1 (<15)	5.183	3.05***	Age 1 (<15)	2.237	1.35
Age 2 (15–24)	8.919	3.89***	Age 2 (15–24)	8.386	3.16***	Age 2 (15–24)	3.617	1.42
Age 3 (25–34)	9.031	3.85***	Age 3 (25–34)	8.630	3.20***	Age 3 (25–34)	3.722	1.44
Age 4 (35–44)	6.095	3.81***	Age 4 (35–44)	5.917	3.24***	Age 4 (35–44)	2.551	1.46
Age 5 (45–54)	0.112	1.74*	Age 5 (45–54)	0.245	3.93***	Age 5 (45–54)	0.105	1.89*
Age 6 (55–64)	−8.919	−3.89***	Age 6 (55–64)	−8.386	−3.16***	Age 6 (55–64)	−3.617	−1.42
Age 7 (>64)	−20.998	−3.86***	Age 7 (>64)	−19.974	−3.19***	Age 7 (>64)	−8.614	−1.43

Notes: *, ** and *** represent 10%, 5% and 1% significance levels, respectively. t values for the long-run coefficients and age distribution coefficients were computed by delta method.

estimated coefficients for the adjustment parameters are significantly negative across the three types of hospitals, indicating that the ARDL models used to investigate cointegrating (ie, long-run) relationships among the examined variables are stably dynamic systems. Furthermore, R^2 (adjusted R^2) ranges from 95.39% to 97.57% (95.18% to 97.18%) were obtained across three types of hospitals, and all model specification tests for the null hypotheses of independence, homogeneity, and normality in residuals were not rejected (reported in Panel C of Table 3). These results collectively suggest a high level of goodness-of-fit for the data from the ARDL models. Furthermore, we found that the linear and quadratic transformations of age distribution are significantly associated with the effectiveness of hospitals' nurse staffing policy at medical centers and regional hospitals, whereas this association is insignificant at district hospitals. Inpatient care reimbursement payments per diem are negatively associated with the effectiveness of hospitals' nurse staffing policy at regional and district hospitals and have no significant impact at medical centers. Real monthly regular earnings in the healthcare industry generate no significant effect on the effectiveness of hospitals' nurse staffing policy, but business cycles negatively impact the effectiveness of hospitals' nurse staffing policy at all types of hospitals. The estimated coefficients for the shares of the population are only significant for the share of the population aged 45–54 at district hospitals, but the shares of the population in all age-specific groups have significant impacts on the effectiveness of hospitals' nurse staffing policy at medical centers and regional hospitals.

Figures 2A–C further illustrate downward trends in the effect of age distribution on the effectiveness of hospitals' nurse staffing policy. Specifically, the shares of the population belonging to the two older age groups (the elderly (age ≥ 65) and those aged 55–64) have negative effects on the effectiveness of hospitals' nurse staffing policy at medical centers and regional hospitals, while the shares of the population in the other five younger groups are positively correlated with the effectiveness of hospitals' nurse staffing policy at medical centers and regional hospitals. The downward trend of the effect of age distribution on the effectiveness of hospitals' nurse staffing policy at district hospitals is found to be insignificant.

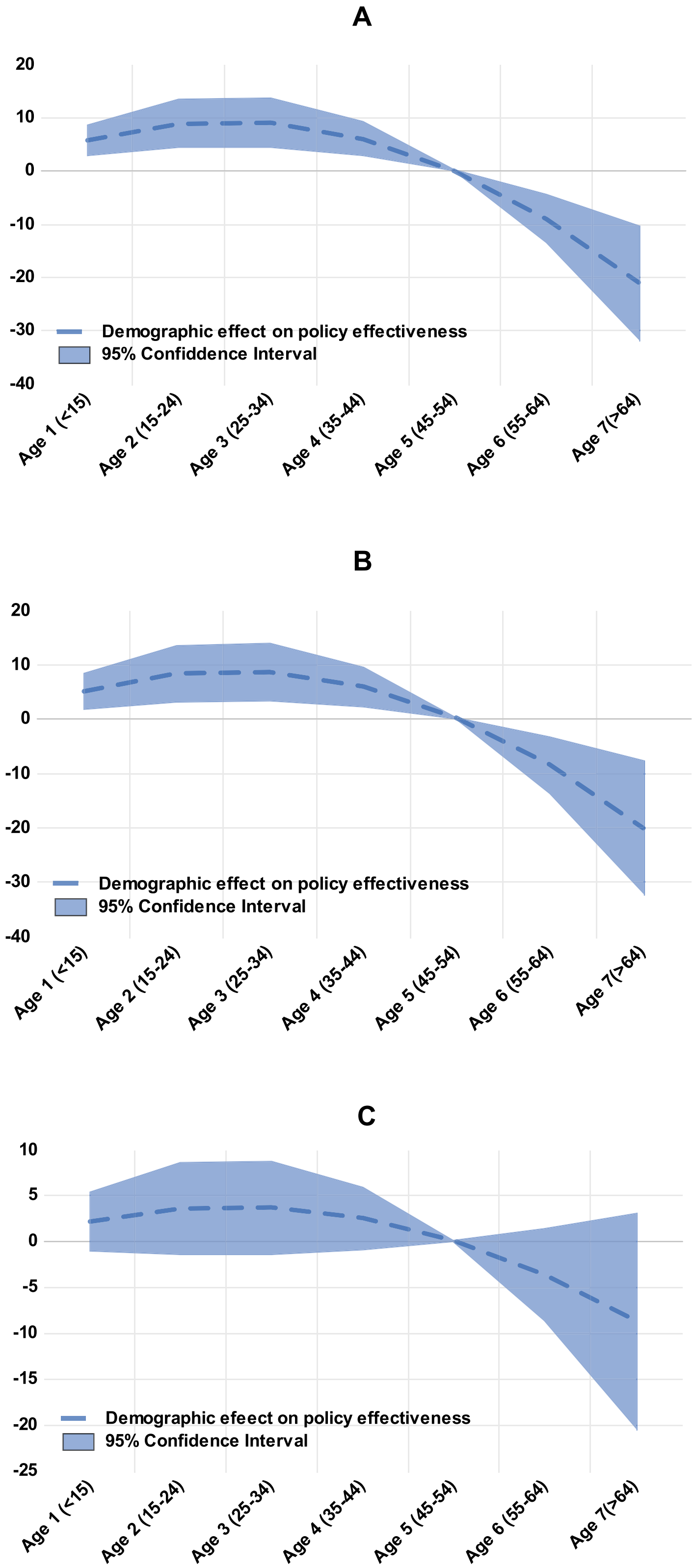

Figure 2 Association between demographic structural change and effectiveness of hospital nurse staffing policy.

Notes: Sub-figures (**A**–**C**) illustrate the relationship between demographic structural change and effectiveness of hospital nurse staffing policy at medical centers, regional hospitals and district hospitals, respectively.

Discussion

Key Results & Policy Implications

The research aim to investigate the relationship between demographic structural changes and the effectiveness of hospital nurse staffing policy. Evidence from Figures 1, 2 and Table 4 indicate a positive association between *PNR* and 14-day readmission rate across various types of hospitals. Nevertheless, the effectiveness of hospitals' nurse staffing policy is observed to diminish with population aging, particularly evident in medical centers and regional hospitals. Several policy implications generated from our results merit attention. First, it is noteworthy that the TV-IRA reveals a positive relationship between *PNR* and the 14-day readmission rate across the three types of hospitals (see Figures 1A–C). These findings suggest that a lower *PNR* is associated with higher inpatient care quality. Notably, these results not only justify the intention of the nurse staffing policy set by the Taiwan government to improve inpatient care quality through reducing the *PNR*, but they also align with those from previous studies investigating the association between nurse staffing and healthcare quality.[12,18–20,22,25,27,47]

Second, considering the significant and positive effects of the shares of the population in the childhood (age < 15) and four major working age groups (ie, aged 15–24, aged 25–34, aged 35–44, and aged 45–54 groups) on the effectiveness of hospitals' nurse staffing policy (measured by the cumulative response of the 14-day readmission rate to a standard deviation change in *PNR*) at medical centers and regional hospitals, one may anticipate that the hospital nurse staffing policy (aiming to enhance inpatient care quality by reducing *PNR*) would be more effective at these hospitals when the proportions of children and those belonging to the major working age groups expand. Nevertheless, the shares of the population belonging to the two older age groups (55–64 and the elderly (age ≥ 65)) yield significantly negative effects on the effectiveness of hospitals' nurse staffing policy, suggesting that the hospital nurse staffing policy would be less effective when the share of those aged 55 years or above increases. These findings diverge from prior research examining the influence of structural age transitions on responses to hospital outpatient copayments. Previous investigations have suggested that population aging enhances the effectiveness of hospital outpatient copayment policies. For instance, Lin et al[38] posit that population aging strengthens the effectiveness of outpatient copayment policies in Taiwan due to heightened price sensitivity among the elderly, who tend to utilize outpatient care services a substantial amount. In contrast, it is anticipated that population aging may attenuate the impact of nurse staffing policies. This expectation arises from the premise that an aging population creates increased demand for inpatient care services, thereby necessitating higher levels of nurse staffing in hospitals.

Third, the impact of population aging on diminishing the effectiveness of hospitals' nurse staffing policy exhibits greater significance in medical centers and regional hospitals compared to district hospitals, as depicted in Figures 2A–C. This discrepancy can be attributed to the specialized roles of regional hospitals and medical centers, catering to tertiary care and handling complex illnesses, respectively.[27,47] Consequently, a substantial proportion, approximately 79%, of inpatient care services are delivered by medical centers and regional hospitals, which also employ around 32% of the entire nursing workforce.[55] This discernible effect of population aging on the effectiveness of healthcare policies is further corroborated in the context of copayment policies for emergency department visits within medical centers.[39] Accordingly, targeted strategic interventions encompassing elements such as ensuring safety in practice, fostering mutual respect, providing adequate facilities, offering necessary support, facilitating continuing education, ensuring an ample supply of resources, maintaining appropriate staffing levels, and ensuring fair remuneration are imperative.[56] These interventions should be specifically directed towards medical centers and regional hospitals to effectively address and mitigate the challenges arising from population aging, thereby enhancing effectiveness of hospitals' nurse staffing policy.

Further Reflection for Policy Implications

It is important to address that our Discussion on the above policy implications should further reflect on the clinical settings of nurse staffing policy and the sensitivity of patient outcome measures. The former should be rooted in well-established evidence on the optimal safe nurse staffing levels per care setting, striking the golden balance between cost-effectiveness and cost-efficiency and satisfying many key decision-makers such as nurses, healthcare institution stakeholders, patients, and caregivers.[31,32,57,58] The exclusion of these key decision-makers from nursing workforce policymaking is likely the main reason why the nursing shortage in clinical settings continues to worsen,[57,58] despite the implementation of many targeted strategic interventions based on hospital nurse staffing literature.[12,18–20,22,25,27,47] Regarding the sensitivity of patient outcome measures, it is recognized that utilizing the 14-day readmission rate as a gauge of inpatient care quality would be intricate due to its susceptibility to various patient characteristics. Factors such as the severity of illness, chronicity of the underlying condition, comorbidity levels, and the extent of social support significantly influence the likelihood of readmission.[46]

Given that individuals aged 55 years or older are prone to experiencing multiple health issues, thereby increasing the likelihood of readmission, merely increasing the number of nurses for this population may not substantially decrease their readmission rates. Moreover, while individuals in these age groups may frequently seek medical care at medical centers and regional hospitals for managing chronic conditions,[55] they are most likely to be readmitted to district hospitals nearer to their residences when necessary. Hence, it is essential to consider a potential caveat in our discussion: population aging may diminish the effectiveness of nurse staffing policies.

Economic Incentives & Business Cycles

The inpatient care reimbursement payments per diem serve as a metric for hospital competition within Taiwan's healthcare system, which operates under the NHI program. This system utilizes a global budgeting payment scheme to reimburse hospitals for their services.[27] Notably, the total number of hospitals fluctuated between 480 and 494, while the total number of medical centers remained constant at 19 throughout the study period.[55] Since each type of hospitals competes for its own share of the healthcare budget, this observation implies that competition among medical centers is considerably lower than that among regional and district hospitals. Consequently, the observed negative correlation between the inpatient care reimbursement payments per diem and the effectiveness of hospitals' nurse staffing policy at regional and district hospitals indicates that heightened competition under the global budgeting payment scheme is likely to undermine the effectiveness of hospitals' nurse staffing policy. Additionally, it is important to address the fact that the income level of healthcare workers, as measured by real monthly regular earnings in the healthcare industry, does not exert any discernible impact on the effectiveness of hospitals' nurse staffing policy across all types of hospitals, as evidenced by the results presented in Table 4. Therefore, in the realm of policy instrument choices that significantly influence the effectiveness of hospitals' nurse staffing policy, priority should be accorded to instruments that shape hospital behavior, such as augmenting reimbursement payments based on *PNR*, as opposed to individual economic incentives for nurses seeking employment at hospitals.

The markedly negative effects of business cycles (measured using the composite leading indicator) on the effectiveness of hospitals' nurse staffing policy, as identified in Table 4, suggest that periods of economic prosperity are likely to undermine the effectiveness of hospitals' nurse staffing policy. This negative association emanates from both the supply side of nurses and the demand side of healthcare services. On the supply side, during economic booms, there is an elevated likelihood of nursing staff transitioning to alternative professions.[59] On the demand side, previous studies examining the relationship between business cycles and health conditions indicate that better economic conditions are correlated with poorer health conditions and an increased demand for healthcare services.[39,60,61]

Limitations of Study

It is imperative to delineate several research limitations to ensure comprehensive understanding of this study. The primary limitation inherent in our investigation pertains to the time-series methodology employed to examine the impact of demographic changes on the effectiveness of hospitals' nurse staffing policy for inpatient care. It is crucial to acknowledge that the age distribution and inpatient care quality utilized in our analyses are based on aggregated data. Consequently, the empirical results derived from our models should not be extrapolated to individual behavior changes at specific ages in response to *PNR* adjustments in hospitals, in order to mitigate the risk of ecological fallacies.[62] Second, despite the frequent use of the 14-day readmission rate as an indicator of inpatient care quality,[27,45,46] it is important to recognize that the likelihood of 14-day readmission may be particularly sensitive within the older population, who are more likely to experience severe illness, multiple chronic conditions, and pronounced comorbidity levels.[46] Consequently, we have advocated for prudence in our discussion regarding the interplay between demographic structural changes and the effectiveness of nurse staffing policy for inpatient care.

Thirdly, beyond demographic changes, numerous factors such as the physical and mental health status of nursing staff, working environment conditions, job-seeking behaviors or preferences and cost of inpatient care quality can influence the effectiveness of hospitals' nurse staffing policy. Nevertheless, the time-series data for these variables are not available in the research databases in Taiwan, posing a constraint on the scope of this study. Fourth, similar to other studies in nursing workforce research, this study lacks the capacity to explore the concurrent dynamics of nurse staffing, quality of care, and costs across a continuum of change that determines the optimal safe nurse staffing level. Recent investigations conducted by Park et al have adopted Park's sweet spot theory-driven Artificial Intelligence Algorithm to model the optimal safe nurse staffing zone, which aims to mitigate the limitations of traditional nursing workforce research.[31,32,57,58] This research paradigm, by emphasizing patient outcomes or care quality alongside cost considerations, addresses the shortcomings that have hindered the effective implementation of knowledge into practice and policy.

Directions for Future Research

Based on the aforementioned discussions, it is recommended that future research endeavors focus on two main aspects. First, the application of Park's sweet spot theory-driven Artificial Intelligence Algorithm[30–32,57,58] should be employed to explore the dynamic interactions among nurse staffing, quality of care, and costs across a continuum of change within Taiwan's healthcare system. Second, collecting individual-level data is essential to examine the intricate interactions among hospitals' managerial actions affecting the quality of care, nurses' decisions regarding employment at hospitals and patient outcomes in response to nurse staffing policies within Taiwan's healthcare system.

Conclusion

The primary goal of the hospital nurse staffing policy in Taiwan is to enhance inpatient care quality by increasing the nursing staff level in hospitals. Nevertheless, Taiwan's healthcare system is confronted with significant challenges due to the rapid aging of the population and a sustained decline in birth rates. This dual challenge results in an increasing demand for healthcare services along with a reduction in the nursing workforce, potentially impacting the effectiveness of hospitals' nurse staffing policy. In response to these challenges, this study pioneers the use of TVP-VAR and ARDL models to investigate the impact of demographic changes on the effectiveness of hospitals' nurse staffing policy in Taiwan. The time-varying impulse responses from the TVP-VAR model demonstrate a significantly positive association between *PNR* and 14-day readmission rate across diverse hospital sizes, encompassing medical centers, regional hospitals, and district hospitals. The ARDL model establishes long-term relationships among the effectiveness of hospitals' nurse staffing policy (quantified by the cumulative response of inpatient care quality to adjustments in nurse staffing levels), age distribution, hospital competition, health worker income, and business cycles across all types of hospitals. An essential finding regarding these long-run relationships is the observed diminishing effectiveness of hospitals' nurse staffing policy with population aging, particularly evident in medical centers and regional hospitals. To achieve the targeted objective of the hospital nurse staffing policy, aimed at improving inpatient care quality by reducing the *PNR*, it is strongly recommended, especially in an aging society, to institute mandated *PNR* in medical centers and regional hospitals that are significantly lower than those determined without considerations for demographic structural changes.

Ethics

The data collection process was approved by the Research Ethics Committee of Taichung Tzu Chi Hospital with the Certificate of Exempt Review ID: REC110-23.

Acknowledgments

This research was funded by the National Science and Technology Council in Taiwan for the research project entitled "Now-casting for the effect of nurse staffing on quality of inpatient care during the COVID-19 pandemic outbreak: Evidence from Taiwan" with Grant No. 110-2410-H-025-012.

Disclosure

The authors report no conflicts of interest in this work.

References

1. ICN. Influencing health policy to protect and respect nurses' rights and improve health. International Council of Nurses; 2022. Available from: https://www.icn.ch/resources/publications-and-reports/icn-annual-report-2022-influencing-health-policy-protect-and. Accessed February 28, 2024.
2. Drennan VM, Ross F. Global nurse shortages—the facts, the impact and action for change. *Br Med Bul*. 2019;130(1):25–37. doi:10.1093/bmb/ldz014
3. Finlayson B, Dixon J, Meadows S, Blair G. Mind the gap: the extent of the NHS nursing shortage. *BMJ*. 2002;325(7363):538–541. doi:10.1136/bmj.325.7363.538
4. Fleming P, Thomas S, Williams D, Kennedy J, Burke S. Implications for health system reform, workforce recovery and rebuilding in the context of the Great Recession and COVID-19: a case study of workforce trends in Ireland 2008-2021. *Human Res Health*. 2022;20(1):48. doi:10.1186/s12960-022-00747-8
5. Girardeau M. Nurses' occupational turnover in the Nordics: a mixed method, systematized review; Oslo, Norway: Oslo Metropolitan University; 2022. Available from: https://oda.oslomet.no/oda-xmlui/bitstream/handle/11250/3018075/Girardeau_SIW_2022.pdf?sequence=1&isAllowed=y. Accessed February 28, 2024.
6. Reiff E, Gade C, Böhlich S. Handling the shortage of nurses in Germany: opportunities and challenges of recruiting nursing staff from abroad, IUBH Discussion Papers; Human Resources (3/2020); 2020. Available from: https://www.econstor.eu/bitstream/10419/222921/1/1726039005.pdf. Accessed February 28, 2024.
7. Boamah SA, Callen M, Cruz E. Nursing faculty shortage in Canada: a scoping review of contributing factors. *Nursing Outlook*. 2021;69(4):574–588. doi:10.1016/j.outlook.2021.01.018
8. Yoshioka-Maeda K, Iwasaki-Motegi R, Honda C. Resolution for the severe shortage of nurses for combating COVID-19 in Japan. *Asia Pacif J Public Health*. 2023;35(4):320–321. doi:10.1177/1010539520982489
9. Teng SW. Nursing manpower and solutions in Taiwan. *Hu Li Za Zhi*. 2014;61(2):5–12. doi:10.6224/JN.61.2.5
10. Haddad LM, Annamaraju P, Toney-Butler TJ. Nursing Shortage; Treasure Island (FL), USA: StatPearls Publishing; 2023. Available from: https://www.ncbi.nlm.nih.gov/books/NBK493175/. Accessed February 28, 2024.
11. Nawagi F, Kneafsey R, Modber M, Mukeshimana M, Ndungu C, Bayliss-Pratt L. An overview of nursing and midwifery leadership, governance structures, and instruments in Africa. *BMC Nurs*. 2023;22(1):168. doi:10.1186/s12912-023-01336-3
12. Butler M, Schultz TJ, Halligan P, et al. Hospital nurse-staffing models and patient- and staff-related outcomes. *Cochrane Database Syst Rev*. 2019;4(4):CD007019. doi:10.1002/14651858.CD007019.pub3
13. Everhart D, Neff D, Al-Amin M, Nogle J, Weech-Maldonado R. The effects of nurse staffing on hospital financial performance: competitive versus less competitive markets. *Health Care Manage Rev*. 2013;38(2):146–155. doi:10.1097/HMR.0b013e318257292b
14. Shin S, Park JH, Bae SH. Nurse staffing and nurse outcomes: a systematic review and meta-analysis. *Nursing Outlook*. 2018;66(3):273–282. doi:10.1016/j.outlook.2017.12.002
15. Chen C, Meier ST. Burnout and depression in nurses: a systematic review and meta-analysis. *Internat J Nurs Stud*. 2021;124:104099. doi:10.1016/j.ijnurstu.2021.104099
16. Marufu TC, Collins A, Vargas L, Gillespie L, Almghairbi D. Factors influencing retention among hospital nurses: systematic review. *Br J Nurs*. 2021;30(5):302–308. doi:10.12968/bjon.2021.30.5.302
17. Du J, Zhang L, Xu C, Qiao J. Relationship between the exposure to occupation-related psychosocial and physical exertion and upper body musculoskeletal diseases in hospital nurses: a systematic review and meta-analysis. *Asian Nurs Res*. 2021;15(3):163–173. doi:10.1016/j.anr.2021.03.003
18. Twigg DE, Kutzer Y, Jacob E, Seaman K. A quantitative systematic review of the association between nurse skill mix and nursing-sensitive patient outcomes in the acute care setting. *J Adv Nurs*. 2019;75(12):3404–3423. doi:10.1111/jan.14194
19. Griffiths P, Recio-Saucedo A, Dall'Ora C, et al.; Missed Care Study Group. The association between nurse staffing and omissions in nursing care: a systematic review. *J Adv Nurs*. 2018;74(7):1474–1487. doi:10.1111/jan.13564
20. Van T, Annis AM, Yosef M, et al. Nurse staffing and healthcare-associated infections in a national healthcare system that implemented a nurse staffing directive: multi-level interrupted time series analyses. *Internat J Nurs Stud*. 2020;104:103531. doi:10.1016/j.ijnurstu.2020.103531
21. Drennan J, Murphy A, McCarthy VJC, et al. The association between nurse staffing and quality of care in emergency departments: a systematic review. *Internat J Nurs Stud*. 2024;153:104706. doi:10.1016/j.ijnurstu.2024.104706
22. Numata Y, Schulzer M, van der Wal R, et al. Nurse staffing levels and hospital mortality in critical care settings: literature review and meta-analysis. *J Adv Nurs*. 2006;55(4):435–448. doi:10.1111/j.1365-2648.2006.03941.x
23. Blatter C, Osińska M, Simon M, Zúñiga F. The relationship between nursing home staffing and resident safety outcomes: a systematic review of reviews. *Internat J Nurs Stud*. 2024;150:104641. doi:10.1016/j.ijnurstu.2023.104641
24. Clemens S, Wodchis W, McGilton K, McGrail K, McMahon M. The relationship between quality and staffing in long-term care: a systematic review of the literature 2008-2020. *Internat J Nurs Stud*. 2021;122:104036. doi:10.1016/j.ijnurstu.2021.104036
25. Aiken LH, Sloane DM, Bruyneel L, et al. Nurse staffing and education and hospital mortality in nine European countries: a retrospective observational study. *Lancet*. 2014;383(9931):1824–1830. doi:10.1016/S0140-6736(13)62631-8
26. Shin S, Park JD, Shin JH. Improvement Plan of Nurse Staffing Standards in Korea. *Asian Nurs Res*. 2020;14(2):57–65. PMID: 32305508. doi:10.1016/j.anr.2020.03.004
27. Chen WY. On the relationship among nurse staffing, inpatient care quality and hospital competition under the global budget payment scheme in Taiwan's National Health Insurance system: mixed Frequency VAR analyses. *Systems*. 2022;10(5):187. doi:10.3390/systems10050187
28. de Cordova PB, Pogorzelska-Maziarz M, Eckenhoff ME, McHugh MD. Public reporting of nurse staffing in the United States. *J Nurs Regul*. 2019;10(3):14–20. doi:10.1016/S2155-8256(19)30143-7

29. Juraschek SP, Zhang X, Ranganathan V, Lin VW. United States registered nurse workforce report card and shortage forecast. *Am J Med Qual*. 2019;34(5):473–481. doi:10.1177/1062860619873217
30. JEC REPUBLICANS. The consequences of declining fertility for social capital. Joint Economic Committee Republicans; 2022. Available from: https://www.jec.senate.gov/public/_cache/files/635c69dc-6a5a-467b-b7b0-3ab906fb4a94/the-consequences-of-declining-fertility-for-social-capital.pdf. Accessed June 17, 2024.
31. Park CS. "More is not always better": park's sweet spot theory-driven implementation strategy for viable optimal safe nurse staffing policy in practice. *Internat Nurs Rev.* 2023;70(2):149–159. doi:10.1111/inr.12785
32. Park CS. Optimizing staffing, quality, and cost in home healthcare nursing: theory synthesis. *J Adv Nurs*. 2017;73(8):1838–1847. doi:10.1111/jan.13284
33. Chen WY. Demographic structure and monetary policy effectiveness: evidence from Taiwan. *Qual Quantity*. 2017;51(6):2521–2544. doi:10.1007/s11135-016-0407-1
34. Imam P. Shock from graying: is the demographic shift weakening monetary policy effectiveness. *Internat J Finan Econom*. 2015;20:138–154. doi:10.1002/ijfe.1505
35. Singh B. Demographic transition and asset prices: evidence from developing countries. *Internat Finan*. 2019;22(1):53–69. doi:10.1111/infi.12138
36. Giagheddu M, Papetti A. Demographics and the real exchange rate. Available from: http://dx.doi.org/10.2139/ssrn.3358551. Accessed February 28, 2024.
37. Papapetrou E, Tsalaporta P. The impact of population aging in rich countries: what's the future? *J Policy Mode*. 2020;42(1):77–95. doi:10.1016/j.jpolmod.2019.12.002
38. Lin YL, Chen WY, Shieh SH. Age structural transitions and copayment policy effectiveness: evidence from Taiwan's national health insurance system. *Int J Environ Res Public Health*. 2020;17(12):4183. doi:10.3390/ijerph17124183
39. Chen WY, Lin YJ, Yang CH. Effect of demographic structural change on copayment policy effectiveness for emergency department visits. *Taiwan J Public Health*. 2021;40(5):525–544.
40. NDC. Population projections for R.O.C Taiwan. Executive Yuan: National Development Council; 2023. Available from: https://www.ndc.gov.tw/Content_List.aspx?n=D527207EEEF59B9B. Accessed February 28, 2024.
41. Lu MS, Tseng HY, Liang SY, Lin CF. Concept for planning the nurse-patient ratio and nursing fee payment linkage system. *Hu Li Za Zhi*. 2017;64(1):17–24. doi:10.6224/JN.000004
42. TUONA. Taiwan nursing workforce statistics in year 2023. Taiwan: Taiwan Union of Nurses Association; 2023. Available from: https://www.nurse.org.tw/publicUI/H/H10201.aspx?arg=8DAD4B763FABC64071. Accessed February 28, 2024.
43. Nakajima J. Time-varying parameter VAR model with stochastic volatility: an overview of methodology and empirical applications. *Monet Economic Stud*. 2011;29:107–142.
44. Pesaran MH, Shin Y, Smith RJ. Bounds testing approaches to the analysis of level relationships. *J Appl Economet*. 2001;16(3):289–326. doi:10.1002/jae.616
45. Chen WY, Lin FL. On the asymmetric relationship between physician mental health disorders on quality of healthcare under the COVID-19 pandemic in Taiwan: quantile on Quantile regression analyses. *Risk Manag Healthcare Policy*. 2023;16:2291–2307. doi:10.2147/RMHP.S429516
46. Clarke A. Readmission to hospital: a measure of quality or outcome? *Qual Saf Health Care*. 2004;13(1):10–11. doi:10.1136/qshc.2003.008789
47. Liang YW, Chen WY, Lee JL, Huang LC. Nurse staffing, direct nursing care hours and patient mortality in Taiwan: the longitudinal analysis of hospital nurse staffing and patient outcome study. *BMC Health Serv Res*. 2012;12(1):44. doi:10.1186/1472-6963-12-44
48. Chen WY. On the network transmission mechanisms of disease-specific healthcare expenditure spillovers: evidence from the connectedness network analyses. *Healthcare*. 2021;9:319. doi:10.3390/healthcare9030319
49. Fair RC, Dominguez KM. Effects of the changing U.S. age distribution on macroeconomic equations. *Am Econ Rev*. 1991;81:1276–1294.
50. Chang T, Chen WY. Revisiting the relationship between suicide and unemployment: evidence from linear and nonlinear cointegration. *Econom Syst*. 2017;41(2):266–278. doi:10.1016/j.ecosys.2016.06.004
51. Chen WY, Lin YH. On the relationship between business cycle and fertility rate in Taiwan: evidence from the nonlinear cointegration methodology. *Roman J Econom Forecast*. 2018;21(1):140–156.
52. Perron P. Further evidence on breaking trend functions in macroeconomic variables. *J Econom*. 1997;80(2):355–385. doi:10.1016/S0304-4076(97)00049-3
53. Hansen BE. Approximate asymptotic p values for structural-change tests. *J Busin Econom Stud*. 1997;15(1):60–67. doi:10.2307/1392074
54. Fisher RA. *Statistical Methods for Research Workers*. 11th ed. Edinburgh, UK: Oliver and Boyd; 1925.
55. MOHW. Statistics of Medical Care Institution & Hospital Utilization. Executive Yuan, Taiwan: Ministry of Health and Welfare; 2023. Available from:https://dep.mohw.gov.tw/DOS/lp-5099-113.html. Accessed February 28, 2024.
56. Slatyer S, Coventry LL, Twigg D, Davis S. Professional practice models for nursing: a review of the literature and synthesis of key components. *J Nurs Manag*. 2016;24(2):139–150. doi:10.1111/jonm.12309
57. Park CS, Kabak M, Kim H, Lee S, Cummings GG. No more unimplementable nurse workforce planning. *Contemp Nurse*. 2022;58(2–3):237–247. doi:10.1080/10376178.2022.2056067
58. Park CS. Challenging rules, creating values: park's sweet spot theory-driven central-'optimum nurse staffing zone'. *J Adv Nurs*. 2018;74(6):1231–1232. doi:10.1111/jan.13496
59. Aslim E, Chou SY, De K. Business cycles and healthcare employment. *Nat Bur Econ Res Work Paper Ser*. 2022;2022:29799.
60. Chang DS, Chen Y, Tsai YC. How injury incidence is associated with business cycles? empirical evidence from Taiwan. *Safety Science*. 2018;110:235–248. doi:10.1016/j.ssci.2018.08.014
61. Ruhm CJ. Are recessions good for your health? *Q J Econ*. 2000;115(2):617–650. doi:10.1162/003355300554872
62. Robinson WS. Ecological correlations and the behavior of individuals. *Am Sociological Rev*. 1950;15(3):351–357. doi:10.2307/2087176