Scientific and Social Research, 2023, Volume 5, Issue 12
https://ojs.bbwpublisher.com/index.php/SSR

Impact of Medical Resources on Infant Mortality: Taking Yunnan Province as an Example

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Abstract: In this study, the autoregressive distributed lag model (ARDL) was used to estimate the long-term impact of the number of health medical institutions and health technicians (two important indicators in medical resources) on infant mortality in Yunnan Province. The error correction model (ECM) was used to estimate the short-term impact influence. The results show that the number of health and medical institutions has a significant positive long-term and short-term impact on infant mortality; the number of health workers has a significant negative short-term impact and a significant positive long-term impact on infant mortality. Several suggestions are also provided to optimize the allocation of medical resources and policy construction. For example, medical institutions should be built and health workers should be recruited judiciously, focusing on "quality" rather than "quantity." In addition, this study also provides empirical evidence for future research in related fields.

Keywords: Medical resources; Number of health and medical institutions; Number of health workers; Infant mortality rate

Online publication: December 27, 2023

1. Introduction

Infant mortality rate is one of the three major indicators to measure the health level of residents of a country or region (the other two indicators are average life expectancy and maternal mortality rate). In addition, it can also reflect the level of socio-economic development [1]. Therefore, the study of infant mortality has always been a topic worthy of attention, such as its decline pattern, future development trends, and differences between different regions [2]. Although the public health infrastructure in western cities is poor [3], the infant mortality rate in Yunnan Province has been significantly reduced in the past three decades, from 4.64% in 1992 to 0.61% in 2021 (data source: Yunnan Statistical Yearbook). The reason for the steady decline in infant mortality is the equalization of pediatric resources among regions and the improvement in the overall utilization of pediatric medical resources [4]. Infant mortality is also closely related to economic development [5]. In other words, medical and health resources and socioeconomic status are important factors affecting infant mortality [6]. Therefore, this study uses the number of healthcare institutions and health workers in Yunnan Province as independent variables to represent medical resources and the Gross Domestic Product (GDP) of Yunnan Province as a control variable to represent socioeconomic conditions. In addition, EViews10 software was used for analysis because this software has greater advantages than SPSS software for time series data analysis. Time series analysis is more applicable for researching infant mortality and it can be used to guide the government work and evaluation policy [7].

2. Empirical analysis

2.1. Model specification

This study uses 30 years of annual time series data from 1992 to 2021 in Yunnan Province. The data are mainly extracted from the Yunnan Statistical Yearbook.

This article aims to estimate the impact of the number of health and medical institutions and health workers on infant mortality in Yunnan Province. A linear model specification equation was constructed as shown in Equation (1), with all variables in logarithmic form.

$$IMR_t = \beta_0 + \beta_1 HMI_t + \beta_2 HW_t + \beta_3 GDP_t + \varepsilon_t \tag{1}$$

Among them, *IMR* (infant mortality rate) is the infant mortality rate in Yunnan Province, which acts as the dependent variable; *HMI* (health and medical institution) is the number of health and medical institutions in Yunnan Province, and *HW* (health workers) is the number of health workers in Yunnan Province, which act as independent variables; *GDP* is the gross domestic product of Yunnan Province, used as a control variable; ε_t is the error term.

2.2. Unit root test

The Dickey-Fuller (ADF) and the Phillips-Perron (PP) unit root tests were performed to test the stationarity of all the above variables to ensure that all variables' levels or first differences were stationary. Then, an autoregressive distributed lag model (ARDL) could be constructed. The purpose of using two detection methods is to avoid the existence of potential unit roots.

2.3. ARDL

$$\begin{aligned}\Delta IMR_t = {} & \theta_0 + \beta_1 IMR_{t-1} + \beta_2 HMI_{t-1} + \beta_3 HW_{t-1} + \beta_4 GDP_{t-1} \\ & + \sum_{i=1}^{p} \theta_1 \Delta IMR_{t-1} + \sum_{j=0}^{q} \theta_2 \Delta HMI_{t-j} + \sum_{k=0}^{r} \theta_3 \Delta HW_{t-k} + \sum_{l=0}^{s} \theta_4 \Delta GDP_{t-l} + e_t\end{aligned} \tag{2}$$

In Equation (2), $\Delta IMR_t = IMR_t - IMR_{t-1}$; β_1, β, β_3, and β_4 are equivalent to the coefficients of the long-term relationship; p, q, r, s indicates different lag lengths of variables, and the specific values were determined by testing with EViews10; e_t is the "white noise" error term. In addition, a cointegration test was performed to determine whether there was a long-term relationship between the variables.

2.4. Diagnostic tests

Diagnostic tests were performed to ensure the entire model and empirical analysis were valid and feasible. In this study, two diagnostic tests were used:

(1) Error sequence autocorrelation detection

A Brush-Grodfrey LM test was performed to ensure that the errors in the model were sequence-independent. Two lag specifications were selected for inspection: LM lag specifications were 2 and 4. In this test, if the *P-value* is greater than 0.05, the model errors are serially independent, and there is no serial correlation problem; if the *P-value* is less than 0.05, there is a serial correlation problem.

(2) Model dynamic stability detection

The cumulative sum (CUSUM) and CUSUM of square (CUSUMQ) tests were carried out to ensure the model was stable, and the experimental results were observed. If the blue line was within the red line (solid line within the dashed line), the model was considered dynamically stable. As long as one of the tests achieved the expected results, the model was considered stable.

2.5. ECM

After performing diagnostic checks and the results of long-term effects (cointegration tests) were meaningful, short-term relationships could be evaluated. In this step, an ECM was established to estimate the short-term relationship, as shown in Equation (3).

$$\Delta IMR_t = \chi + \alpha ECT_{t-1} + \sum_{i=1}^{p-1} \theta_1 \Delta IMR_{t-1} + \sum_{j=0}^{q-1} \theta_2 \Delta HMI_{t-j} + \sum_{k=0}^{r-1} \theta_3 \Delta HW_{t-k} + \sum_{l=0}^{s-1} \theta_4 \Delta GDP_{t-l} + e_t \tag{3}$$

In Equation (3), ECT_{t-1} is the error correction term, and θ_1, θ_2, θ_3, *and* θ_4 are equivalent to the coefficients of the short-term relationship.

3. Result analysis

3.1. Unit root test

Table 1. ADF unit root test

	Level		1st Difference	
	Trend	No trend	Trend	No trend
IMR	-2.186	-0.057	-5.601***	-5.746***
HMI	-2.342	-1.219	-5.266***	-5.353***
HW	-0.686	2.013	-4.019**	-3.381**
GDP	-2.556	-0.378	-3.158*	-3.369**

Note: *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Table 2. PP unit root test

	Level		1st Difference	
	Trend	No trend	Trend	No trend
IMR	-2.217	-1.146	-5.305***	- 5.393 ***
HMI	-2.432	-1.870	-9.362***	-9.357***
HW	-0.790	1.480	-4.019**	- 3.348**
GDP	-2.584	-1.595	-3.173*	- 3.374**

Note: *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Table 1 and **Table 2** reveal that in the first-order difference unit root test, *IMR* and *HMI* rejected the null hypothesis (having a unit root) at the 10% level, while *HW* and *GDP* rejected the null hypothesis at the 5% level. Consequently, the first differences of all variables were stationary, allowing for the application of the ARDL model for cointegration testing.

3.2. Long-term coefficient estimation

Table 3. Long-term coefficient estimates and cointegration tests

Variable	Coefficient	*t*	*P*
C	-2.144	-1.161	0.258
HMI	0.102**	-2.289	0.024
HW	0.357**	-2.303	0.023
GDP	-0.797***	-7.171	0.000
Optimal lag length	(1,1,1,0)	F	7.604
Critical value			

Significant level	Lower bound	Upper bound
10%	2.37	3.2
5%	2.79	3.67
1%	3.65	4.66

Note: *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels.

As shown in **Table 3**, the *F*-value of the ARDL boundary cointegration test was 7.604, which was greater than the upper bound value of 4.66 at the 1% level, which meant that there was a cointegration relationship between the variables: *HMI* and *HW* had a long-term impact on *IMR*. According to the coefficient, at the 5% level, *HMI* and *HW* significantly impact *IMR*.

3.3. Diagnostic tests

Table 4. Serial autocorrelation test and dynamic stability test

(1) LM serial autocorrelation test			
Hysteresis length: 2			
F	0.3585	Chi-square test *P-value*	0.6054
Hysteresis length: 4			
F	0.8671	Chi-square test *P-value*	0.3211

(2) Dynamic stability inspection	
CUSUM inspection	Stabilize
CUSUM squared test	unstable

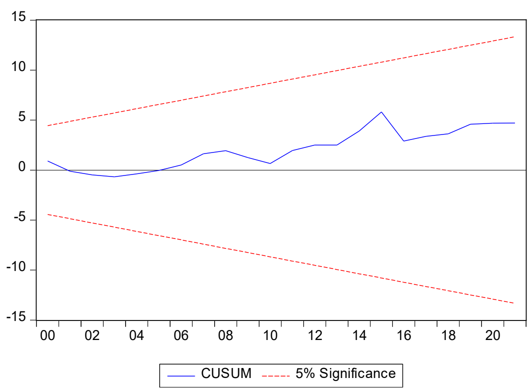

Figure 1. Stability diagnosis

As shown in **Table 4**, the *P-value*s of the chi-square test for lag lengths 2 and 4 were greater than 0.05. Therefore, there was no serial autocorrelation problem in the errors. In addition, as shown in **Figure 1**, the dynamic stability passed the CUSUM test, and the blue line is within the range of the red line (the solid line is within the dotted line). Generally speaking, as long as it passes one of the CUSUM and the CUSUMQ tests, the model can be considered dynamically stable.

3.4. Short-term coefficient estimation

Table 5. Short-term coefficient estimates

Variable	Coefficient	*t*	*P*
C	0.008	0.259	0.7976
ECT_{t-1}	-0.336***	-4.233	0.000
ΔHMI_t	0.143**	2.639	0.014
ΔHW_t	-0.350**	-2.097	0.047
ΔGDP_t	-0.328	-1.705	0.101

Note: *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels.

Table 5 shows the results of the short-term relationship ECM, where the error correction term (ECT_{t-1}) was negative and significant at the 1% level, so the short-term dynamic effect exists. At the 5% level, *HMI* had a significant positive impact on *IMR; HW* had a significant negative impact on *IMR*.

In addition, the coefficient of the error correction term was -0.336, which means that the short-term deviation from the long-term equilibrium could be corrected by 33.6% in one year. Therefore, any short-term deviation will take approximately three years to adjust to the long-term equilibrium.

4. Discussion and policy implications

In Yunnan Province, the number of health and medical institutions and the number of health workers have significant long-term and short-term effects on infant mortality. Specifically, the increase in the number of health and medical institutions has a significant positive impact on infant mortality, which means that an increase will lead to a decrease in infant mortality.

In Yunnan Province, the number of healthcare institutions and healthcare professionals has a significant long-term and short-term impact on the infant mortality rate. Specifically, the number of healthcare institutions has a significant positive effect on the infant mortality rate, indicating that an increase in the number of healthcare institutions leads to an increase in the infant mortality rate. Additionally, the number of healthcare professionals has a significant short-term negative impact and a long-term positive impact on the infant mortality rate. This implies that an increase in healthcare professionals is beneficial for controlling and reducing the infant mortality rate in the short term. However, from a long-term perspective, especially after three years, a continuous increase in healthcare professionals will result in an increase in the infant mortality rate, and this impact may even be greater than the increase in the number of healthcare institutions.

The empirical analysis results of this study can aid local governments in Yunnan Province in optimizing the allocation of medical resources. For example, there is no need to increase the number of health and medical institutions because the increase in health and medical institutions will not help reduce infant mortality. Instead, more should be done to optimize and improve the technologies used in existing medical institutions. Under certain circumstances, some health and medical institutions with unreasonable allocation plans can be disbanded or dismantled. More health workers should be recruited within three years, and reasonable personnel allocation should be carried out based on the medical development status of each region. However, beyond this three-year period, recruitment of health workers must be suspended. In the long run, an increase in the number of health technicians may have a negative impact on reducing infant mortality. Therefore, for the healthy development of Yunnan Province, it is imperative to focus on maintaining the current quantity of medical resources while emphasizing qualitative improvement to ensure the maintenance or reduction of the infant mortality rate.

5. Limitations and recommendations

Due to missing data and the fact that the data has not been updated, this study only used 30 years of annual data from 1992 to 2021. Leveraging the advantages of time series data, future research can utilize new data to consistently assess the impact of medical resources on infant mortality and continually refine the model.

In addition, the research scope of this study only covers Yunnan Province, and data from other provinces in China have yet to be analyzed. Therefore, whether the study of the impact of medical resources on infant mortality applies to all provinces across the country requires more in-depth research.

Funding

The work was funded by the Yunnan Province Philosophy and Social Sciences Planning Project (YB2018007).

Disclosure statement

The authors declare no conflict of interest.

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