Journal of Developing Economies Vol. 9 No. 1 (2024): 1-26

JDE
Journal of Developing Economies

JOURNAL OF DEVELOPING ECONOMIES
https://e-journal.unair.ac.id/JDE/index

THE ROLE OF SOCIOECONOMIC AND FEMALE INDICATORS ON INFANT MORTALITY IN WEST NUSA TENGGARA: A PANEL VECM ANALYSIS

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ABSTRACT

West Nusa Tenggara Province has an infant mortality rate that surpasses the national average. Additionally, it is also characterized as having a high Gini ratio and gender inequality index. Therefore, this study aims to examine the differences in classification among different regions, the long-term and short-term impact, and the causal relationship between socio-economic factors and female indicators in relation to infant mortality. This study used the co-integration method of the panel VECM and applied the natural breaks (Jenks) classification method based on panel data from 10 regencies/ cities in West Nusa Tenggara Province between 2012 and 2022. This study discovered two instances of co-integration where the life expectancy of women was found to have a negative impact, while the percentage of women working full-time was found to have a positive impact on the long-term infant mortality rate. Infant mortality rates in the short term showed a significant relationship with the cointegration coefficient, mean years of schooling of women, life expectancy of women, and percentage of women working full-time. There is a direct causal relationship between the mean years of schooling of women and *the percentage of people living in poverty and the infant mortality rate. This study is expected to serve as a basis to guide the Government of West Nusa Tenggara Province in promoting equity in education, equal job opportunities, adequate healthcare facilities, and increased investment to decrease infant mortality.*

Keywords: *Socioeconomic, Panel VECM, Female Indicator, Infant Mortality Rate, West Nusa Tenggara*

JEL: I15; I25; J13

ARTICLE INFO

Received: December 31th, 2023
Revised: March 1st, 2024
Accepted: March 22th, 2024
Online: June 4th

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To cite this document: Arini, R. P., Mumtazah, S. A., Siahaan, R. M., & Kartiasih, F. (2024). The Role of Socioeconomic and Female Indicators on Infant Mortality in West Nusa Tenggara: A Panel VECM Analysis. *Journal of Developing Economies*, *9(1),* 1-26 https://doi.org/10.20473/jde.v9i1.53416

Introduction

The issue of infant or child mortality under one year of age is a major concern in both developing and underdeveloped countries. It is a complex issue as 50% of the socio-economic factors are directly and indirectly related to infant mortality (Aurellia et al., 2023; Hardinata et al., 2023; Prawidia et al., 2023; Taramsari et al., 2021). According to the OECD & World Health Organization (2020), “Infant mortality reflects the social, economic, and environmental factors affecting both the baby and the mother”. This is supported by the evidence that some countries in the Southeast Asian region, such as Cambodia, Myanmar, and the Philippines, have infant mortality rates three times higher in poor areas compared to rich areas, as described in previous studies. The best indicator of infant mortality rate (IMR) is effective in elucidating the socio-economic development by considering the standards of living, health, and socio-economic conditions in a country (Miladinov, 2020). Several studies in various countries have been carried out to determine the effects of socio-economic factors on infant mortality and found that regions that are economically poor and have high levels of racism tend to have high infant mortality rates. (Asif et al., 2022; Bishop-Royse et al., 2021; Erdoğan et al., 2013; Patel et al., 2021). Therefore, it is necessary for the government to take appropriate measures in formulating policies to reduce infant mortality rates.

The United Nations (UN) launched the Sustainable Development Goals (SDGs) in 2015, which include targets that must be achieved by governments in their efforts to improve human well-being, including reducing infant mortality rates. SDG Indicator 3.2 aims to reduce neonatal mortality to 12 deaths per 1,000 live births and under-five mortality to 25 deaths per 1,000 live births. Indonesia has a strong ambition to reduce infant mortality rates, as stated in the Sustainable Development Goals map by the National Development Planning Agency (2021). In contrast to the UN, which does not set specific targets for infant mortality, Indonesia aims to reduce its infant mortality rate to 15.6 deaths per 1,000 live births by 2030, under the business-as-usual (BAU) scheme. Meanwhile, the intervention scenario aims to achieve a neonatal mortality rate of 12 deaths per 1,000 live births by 2030. Nationally, the Indonesian Government aims to achieve its goals using the BAU scheme, which is almost reaching on target. This is shown in Figure 1, where the infant mortality rate in 2021 reached 18.9 deaths per 1,000 live births.

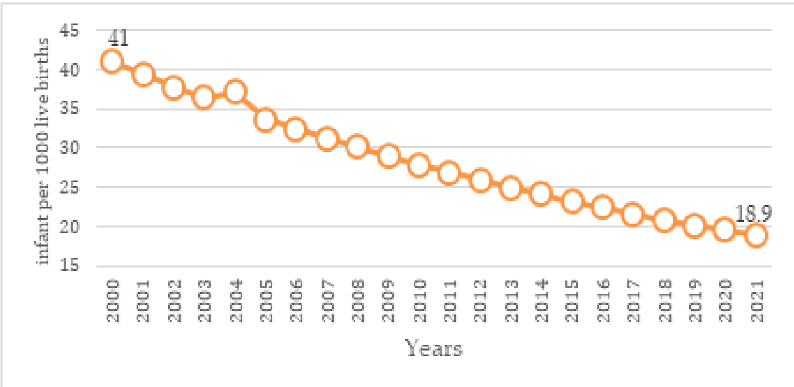

Figure 1: Indonesia’s Infant Mortality Rate (2000-2021)

Source: World Bank (2023)

Indonesia has made significant progress in reducing infant mortality rates nationwide. However, this reduction has not been evenly distributed across all regions of Indonesia. Figure 2 shows that the infant mortality rate in Indonesia is 16.85 deaths per 1,000 live births, with most areas in Java and Bali having rates below the national average, while other regions, such as West Nusa Tenggara, have rates nearly double the IMR of West Java Province. This disparity is inconsistent with the mandate of the Article 28A of the 1945 Constitution of the Republic of Indonesia, which states that, “Every person has the right to life and the right to defend their life and livelihood." Therefore, a comprehensive review of regions with disproportionate infant mortality rates compared to the national average is necessary.

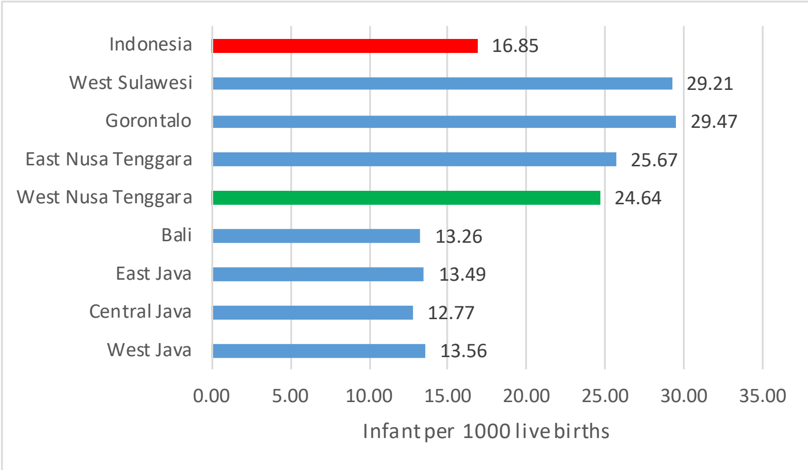

Figure 2: IMR comparison of some provinces in Indonesia

Source: Badan Pusat Statistik (BPS), (2023)

According to the results of the Longform Population Census by the BPS-Statistics Indonesia, West Nusa Tenggara has an infant mortality rate higher than the national average, specifically at 24.67 deaths per 1,000 live births. This number is significantly higher than the targets that Indonesia aims to achieve by 2030. However, in terms of the economy, West Nusa Tenggara is a region with a strong economic growth, as it ranked fourth in 2022 as the province with the highest economic growth in Indonesia. However, this positive aspect contradicts West Nusa Tenggara's status as a region with high inequality, ranking eighth in terms of the highest Gini ratio. This indicates that the high economic growth of West Nusa Tenggara is concentrated in certain regions. This inequality is evidenced by the dominance of investment trends in West Nusa Tenggara by Lombok Island, excessive reliance on the mining sector, and high poverty rates in West Nusa Tenggara (Primadianti & Sugiyanto, 2020). Furthermore, this province has poor gender equality, as seen by its position as the province with the highest Gender Inequality Index in Indonesia, standing at 0.648 in 2022. The highlighted issue in this Inequality Index is the increase in the proportion of married women aged 15-49 years who have not given birth in a healthcare facility (BPS Nusa Tenggara Barat, 2022). Therefore, considering the significant disparity and high gender inequality index, it is necessary to examine the factors contributing to infant mortality in West Nusa Tenggara from a socio-economic and female indicator perspective.

The educational level of parents is a fundamental basis for raising children who prioritize their supervision, ensuring a satisfactory standard of living, nurturing, and sufficient healthcare. Therefore, the higher the level of education, the lower the IMR (Bugelli et al., 2021; Erdoğan et al., 2013). Rahman & Alam (2023) found that an improvement in maternal education will reduce infant mortality rates, while educated fathers will have the awareness to provide adequate nutrition for their children, ensuring their education is guaranteed. Prior research conducted in Indonesia by Schellekens (2021) also demonstrates that high-quality maternal education can account for a 15% reduction in child mortality in Indonesia from 1980 to 2015. Excellent education enables parents to secure a stable and prestigious employment. Households with stable employment have a significant capacity for a life of satisfaction and contentment (Zhang et al., 2022). A working mother can reduce the infant mortality rate (IMR) by having more power to make decisions regarding childcare at home, including providing access to proper healthcare (Asif et al., 2022). This study contradicts the findings of prior studies that showed a higher risk of infant mortality when the mother is employed, attributing it to limitations in the mother's primary caregiving role (Khan & Awan, 2017; Titaley et al., 2008). Meanwhile, life expectancy is closely related to a region's ability to provide good access to healthcare for its residents (Duba et al., 2018). A country with a high life expectancy will have a low infant mortality rate (Wang & Ren, 2019; Zakaria et al., 2020). This is supported by the research conducted by Rahman & Alam (2023), which states that the life expectancy of women is negatively correlated with infant mortality rates. Therefore, from a social perspective and in terms of female indicators, the relationship between female and male education, female life expectancy, and female labor force participation rates will be examined in relation to infant mortality rates in West Nusa Tenggara Province.

Infant mortality rate is significantly associated with both economic growth (Irana et al., 2023) and poverty in a region (Mohamoud et al., 2019). High economic growth improves the living standards in a country (Kartiasih, 2019a; Kartiasih & Setiawan, 2020; Kusumasari & Kartiasih, 2017), thereby reducing infant mortality rates (Abiodun et al., 2020). The Gross Regional Domestic Product (GRDP) per capita indicator can be used to observe economic growth in a particular region as it serves as a catalyst to reduce infant mortality rates (Dutta et al., 2020; Rahman & Alam, 2023). Furthermore, research conducted in East Java on infant mortality also demonstrates the negative influence of GRDP on infant mortality (Putri & Purwanti, 2020). Meanwhile, poverty leads to unequal access to healthcare due to disparities in living standards across different families (Belantika et al., 2023; Pribadi & Kartiasih, 2020; Turner et al., 2020). This has been demonstrated in previous research, where every 1% increase in child poverty leads to a 5.8 increase in infant mortality per 100,000 live births (Taylor-Robinson et al., 2019). Therefore, from an economic perspective, the relationship between GRDP per capita and the percentage of the population living in poverty will be examined in relation to infant mortality rates in West Nusa Tenggara Province.

The objectives of this study are: (1) to understand the classification differences of each variable at the beginning period, end period, or on average in the regencies/cities of West Nusa Tenggara Province; (2) to understanding the long-term and short-term relationships, as well as the causal relationship, between the infant mortality rate variable and other explanatory variables. The classification was made using the natural breaks method to observe any changes in classification throughout the research period (Fariza et al., 2017). The study aims to develop the VECM method proposed by Rashid and Ramirez (2021) using the panel VECM technique, considering the high regional disparities. The use of panel data is more informative as it accommodates heterogeneity, unlike regular time series or cross-sectional data (Chen et al., 2018). The panel vector error correction model (VECM) is advantageous as it is capable of modeling many regions into a single modeling result (Kitessa & Jewaria, 2018).

This study includes a set of novel characteristics that have not been previously used to identify infant mortality rates. Firstly, this study is the only one that identifies infant mortality rates in West Nusa Tenggara Province using a quantitative approach through the panel VECM method. This study aims to provide an update to the research conducted by Demung & Marhaeni (2019), which qualitatively identified the factors causing infant mortality without considering their temporal relationships. Secondly, this study is the first to differentiate the factors causing infant mortality into two conditions, namely long-term and short-term. Thirdly, this study used the most recent and comprehensive data in analyzing the factors causing infant mortality. Therefore, this study is expected to assist the Government of West Nusa Tenggara to formulate effective and efficient policies to reduce infant mortality.

Literature Review

Infant mortality is closely related to the educational variable that the better the educational level of a family, the lower the infant mortality rate (Bugelli et al., 2021; Erdoğan et al, 2013). Educated fathers will have full awareness to carry out nutritional fulfillment for their children, while educated mothers will have a good understanding of childcare (Rahman & Alam, 2023). Previous research using the Fixed Effect Model method on data panels from 38 regencies/cities in Indonesia from 2012 to 2016 showed that women's education in Indonesia had a negative correlation with infant mortality rates (Putri & Purwanti, 2020). Accordingly, we argue that the mean years of schooling of men and women are negatively associated with infant mortality rates.

Previous research by Titaley et al. (2008) showed that families with unemployed fathers and working mothers would increase infant mortality because of the limited duration of exclusive breastfeeding and feeding of babies by mothers, while fathers lost their role in protecting families from poverty. This was supported by a study by Sari & Prasetyani (2021) which, using the Pooled Least Square method in ASEAN countries, including Indonesia, showed that high female labor force participation rates were strongly associated with increased infant mortality rates. These two previous studies are in contrast to a study by Asif et al. (2022) who found that working mothers are able to provide their children with adequate access to healthcare, thereby reducing infant mortality. In addition, a study by Rahman & Alam (2023), using the ARDL and pairwise Granger causality methods, showed that increased female labor participation would reduce infant mortality. We, therefore, hypothesize that the percentage of women working full-time is negatively associated with infant mortality rates.

The life expectancy of women variable clearly reflect the overall mortality rate of the population in a given period of time in a country (Abiodun et al., 2020). High life expectancy indicates that a region has the ability to focus on improving access to healthcare and well-being for its communities. The quality of a country is seen from the life expectancy age of its population, with research in the South Asian region shows that countries with high life expectancy have lower infant mortality rates (Zakaria et al., 2020). This supports a previous study by Wang & Ren (2019) that, based on spatial classification of regions, regions with high infant mortality rates tend to have low life expectancy rates. As a result, we propose that there is a negative correlation between the life expectancy of women and infant mortality rates.

High economic growth in a region increases the standard of living, thereby reducing the infant mortality rate (Abiodun et al., 2020). Poverty in an area leads to limited availability of child health facilities, leading to high infant mortality rates (Mohamoud et al., 2019). GDP per capita is used as a catalyst for economic growth given its impact on infant mortality (Dutta et al., 2020; Rahman & Alam, 2023). Sari & Prasetyani (2021) in their study found that per capita income has a significant negative relationship with infant mortality rates in ASEAN countries. A previous study in East Java by Putri & Purwanti (2020) also found similar results. This suggests that in Indonesia, the better the ability to meet the needs of the family, the lower the impact of infant mortality. Therefore, we postulate that there is a negative correlation between infant mortality rates and GRDP per capita.

Data and Research Methods

Data

This study was conducted using panel data based on the regency/city regions in West Nusa Tenggara Province from 2012 to 2022. The GRDP, MYSWom, MYSMan, and LEWom variables were transformed using natural logarithm to ensure that the variables have a normal distribution during processing (Benoit as cited in Men et al., 2018). This transformation provides robust calculation results (Liang et al., 2015) and maintains stability while improving the linear relationship among the variables (Curran-Everett, 2018). Transformation was not performed on variables that are percentages and proportions.

Table 1: Description of Variables

Variable	Symbol	Description	Source
Infant Mortality Rate	IMR	The number of deaths of infants under one year of age per 1,000 live births	Public Health Office of West Nusa Tenggara
Gross Regional Domestic Product per Capita at Current Market Price	GRDP	The total gross value added produced by the entire economic sector in region (million rupiahs)	BPS-Statistics Indonesia
Women's Mean Years of Schooling	MYSWom	The mean duration of formal education for women (in years)	BPS-Statistics Indonesia
Men's Mean Years of Schooling	MYSMan	The mean duration of formal education for man (in years)	BPS-Statistics Indonesia
Life Expectancy of Women	LEWom	The life expectancy of a newborn girl in a specific year (in years)	BPS-Statistics Indonesia
Percentage of People Living in Poor	P0	Percentage of the population with average per capita expenditure below the poverty line (percent)	BPS-Statistics Indonesia
The Percentage of Women Working Full-Time	LABORWom	Percentage of women aged 15 and above who are employed for more than 35 hours per week (percent)	BPS-Statistics Indonesia

Research Methods

The descriptive analysis in this study used the Natural Breaks (Jenks) classification, which compares the classification of each variable across regencies/cities from 2012 to 2022, and their average, to observe any differences in classification. The use of this classification is designed to obtain the optimal arrangement of data values into different classes (Chen et al., 2013). This classification is capable of grouping datasets based on similar values (Khamis et al., 2018), optimizing the differences between classes, and imposing constraints on variables with significant differences (Zhang et al., 2022). In this study, the authors categorize the classification into three groups due to the limited coverage of regencies/cities in the West Nusa Tenggara Province.

Time series analysis was performed using the panel vector autoregressive (PVAR)/panel vector error correction model (PVECM) to determine short-run and long-run relationships. Additionally, further analysis was performed using the Impulse Response Function (IRF) and Forecast Error Variance Decomposition (FEVD). The use of Panel VAR/VECM is an advancement of the research method used by Rashid & Ramirez (2021) to examine the relationship between Infant Mortality Rate (IMR) and economic growth in India. Several other studies have also employed the PVAR/PVECM method to determine the causal relationship between endogenous and exogenous variables. The research conducted by Kousar et al. (2020) examines the correlation between poverty and energy consumption in the countries of South Asian region, revealing a long-term relationship. In their research, Zhang & Zhang (2021), Ai et al. (2021), and Amaluddin (2020) also employed the PVAR/PVECM method for their analysis.

The analysis using panel VECM began with testing multicollinearity using the cross-sectional dependence (CD) test. This test is used to determine the independence of each variable in the data. After the variables were proven to be independent, the Panel Unit Root test was performed using the Augmented Dickey-Fuller (ADF) test and the Philip Perron (PP) test to avoid spurious regressions between variables. Furthermore, the data were tested with the Optimum Lag Test to determine the optimum lag to be used in this study. Subsequently, the data were tested using the Panel Cointegration test to identify cointegration between variables. If the data were said to be cointegrated, further modeling could be done using panel VECM to determine the long-term relationship between variables. In addition, to identify that the data had a long-term causal relationship, the Panel Granger Causality test was conducted on the data. After modeling, the data were estimated using Impulse Response Function Analysis and Variance Decomposition Analysis.

Cross-Sectional Dependence Test

To conduct a cross-sectional dependence test, Dong et al. (2018) and Akadiri et al. (2020) use the method proposed by Breusch & Pagan (1980) and Pesaran (2004). In this test, the following hypothesis is used.

$$H_0: E(u_{it}u_{jt}) = 0 \forall t, i \neq j \; dan \; H_1: E(u_{it}u_{jt}) \neq 0 \; for \; several \; t, i \neq j$$

In the studies by Dong et al. (2018) and Akadiri et al. (2020), the method proposed by Breusch and Pagan was used to detect cross-sectional dependencies for small N and T with the following equation.

The Breusch & Pagan (1980) method is good for small N and T which can be measured as follows.

$$CD_{BP} = T \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{ij}^2 \tag{1}$$

within

$$\hat{p}_{ij} = \hat{p}_{ji} = \frac{\sum_{t=1}^{T} e_{it} e_{jt}}{\left(\sum_{t=1}^{T} e_{it}^2\right)^{1/2} \left(\sum_{t=1}^{T} e_{jt}^2\right)^{1/2}} \tag{2}$$

In the studies by Dong et al. (2018) and Akadiri et al. (2020), the CD formula developed by Pesaran using the Lagrange multiplier which is good for large N and T is expressed in Equation 3. Unfortunately, the initial formula proposed by Pesaran has limitations, so he proposed a more flexible model for dynamic and stationary models written in the formula in Equation 4. Although the CD test is necessary, it still has the disadvantage that the results may be irrelevant if the error distribution is not symmetrical and the test loses its alternative direction.

$$LM = \sqrt{\frac{T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{ij}^2 - 1 \right) \tag{3}$$

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{ij} \right) \tag{4}$$

Panel Unit Root Test

Stationary data are data that do not fluctuate over a wide range, but fluctuate around a constant mean. The data are constant over time, with no increase or decrease that varies over time. Means and variances that do not change over time indicate a stationary data series (Megaravalli & Sampagnaro, 2018).

Panel VAR/VECM model is a model that requires the principle of cointegration. This principle requires data that are stationary in the first difference. Stationarity in this data targets data that fluctuate around their mean. Estimating a model with two or more non-stationary variables will result in a spurious regression that produces significant parameters, but has no relationship at all in real life (Álvarez-Ayuso et al., 2018). Therefore, when modeling with panel VAR/VECM, it is necessary to check the stationarity of time series data using the Augmented Dickey-Fuller (ADF) test. The equation for performing the ADF test is shown in Equation 5.

$$\Delta Z_{it} = \alpha_0 + \delta Z_{it-1} + x_1 \Delta Z_{it-1} + x_2 \Delta Z_{it-2} + \cdots + x_p \Delta Z_{it-p} + u_{it} \quad (5)$$

where Z_{it} is the time series, α_0 is the intercept, δ is the unit root test coefficient, x_1 until x_p is the augmented first difference, Z_{it} is the lag parameter, and u_{it} is the white-noise error.

Optimum Lag Test

The optimum lag test is important because the panel Granger causality test is quite sensitive to lag length (Mahembe & Mbaya Odhiambo, 2019). Therefore, previous studies determined the optimum lag by comparing not only comparing one evaluation measure, but several evaluation measures, such as LR test, Final Prediction Error (FPE), Akaike Information Criterion (AIC), Schwarz Information Criterion (SC), and Hannan-Quinn Information Criterion (HQ) (Abbas, 2020; Sahoo & Sahoo, 2019).

Panel Cointegration Test

Two or more variables are said to be cointegrated if there is a long-term equilibrium relationship between them (Engle & Granger as cited in Appiah, 2018). The authors employed a research methodology based on the revised approach developed by Johansen and Julius in the 1990s. This methodology is commonly used for conducting co-integration tests and allows for a comprehensive investigation of long-term relationships. It was also used in a previous work by Sharif et al. (2020) to discover cointegration. An arrangement of one or more variables indicates a long-term relationship if all variables are cointegrated and stationary in their first differences (I(1)). If the data are said to be cointegrated, further modeling can be done using panel VECM.

Panel VAR/VECM Model

The structural panel VAR model is an approach that incorporates the response to idiosyncratic and common shocks in Equation 1 (Pedroni, 2013). The VAR model is represented by Equation 6, where is a coefficient matrix with size , is a vector size , and is a vector of deterministic components. Meanwhile, if it is proven that there is cointegration, the modeling is done using the Panel Vector Error-Correction (PVEC) with the model indicated in Equation 2 (Hondroyiannis & Papaoikonomou, 2020). Once the PVAR/PVECM model is formed, the model's feasibility is tested by checking the autocorrelation of the residuals (Portmanteau residual test), the distribution of the errors (residual normality test), and the constancy of the error variance (White test). If the model indicates that there is no autocorrelation in the residuals, the residuals are normally distributed, and the residual variance is constant, then the formed model is considered to be valid.

$$Y_{it} = \delta_i d_t + \sum_{j=1}^{k} \Phi_{ij} Y_{i,t-j} + \varepsilon_{it} \quad (6)$$

$$\Delta Y_{it} = \delta_0 + \Pi_i Y_{i,t-1} + \sum_{j=1}^{k} \Gamma_{ij} \Delta Y_{i,t-j} + \varepsilon_{it} \quad (7)$$

Panel Granger Causality Test

To identify long-term relationships, Su et al. (2021) employed the Granger Causality test in their research to examine the causality between variables. Equation 3 is the mathematical formulation of the Granger causality test.

$$Y_{i,t} = \alpha_i + \sum_{k=1}^{p} \beta_{i,k} Y_{i,t-k} + \sum_{k=1}^{p} \gamma_{i,k} \gamma X_{i,t-k} + \varepsilon_{i,t} \tag{8}$$

Impulse Response Function Analysis dan Variance Decomposition Analysis

The Impulse Response Function is the application of a linear system to identify the direction of an endogenous variable in response to the shock of an exogenous variable at a specific point in time (Boppart et al., 2018). The equation for the impulse response function is written in Equation 4. Furthermore, the general form of Equation 5 can be used to predict the variance error decomposition, which can be used to identify the proportion of directional changes in a variable caused by shocks to that variable as well as shocks to other variables.

$$GI_x(n, \delta_j, \Omega_{t-1}) = E(x_{t+n} \mid \varepsilon_{jt} = \delta_j, \Omega_{t-1}) - E(x_{t+n} \mid \Omega_{t-1}) \tag{9}$$

$$\theta_{ij}^{o}(n) = \frac{\sum_{l=0}^{n} (e_i^{'} A_l P e_j)^2}{\sum_{l=0}^{n} (e_i^{'} A_l \Sigma A_l^{'} e_i)}, \theta_{ij}^{g}(n) = \frac{\sigma_{ii}^{-1} \sum_{l=0}^{n} (e_i^{'} A_l \Sigma e_j)^2}{\sum_{l=0}^{n} e_i^{'} A_l \Sigma A_l^{'} e_i} \tag{10}$$

Findings and Discussion

Classification of Regency/City Territories According to Research Variables

From Figure 3, it can be observed that both on average, at the beginning, and at the end of the period, the majority of regencies/cities in West Nusa Tenggara Province are classified as moderate. The most significant change is observed in Mataram City, where at the beginning of the period, it was classified as an area with low infant mortality rate (IMR), but at the end of the period, it was classified as an area with high IMR. However, Mataram City on average is classified as an area with low IMR, thus the spike at the end of the period does not have a significant impact on its average. There has also been a positive development in West Sumbawa and West Lombok, where at the beginning of the period, they had a moderate classification of infant mortality rate, but at the end of the period, they became regions with low infant mortality rates.

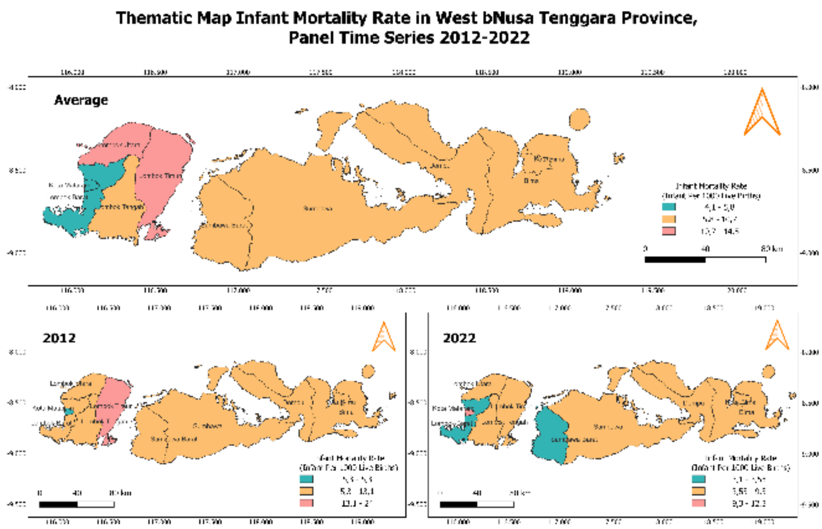

Figure 3: IMR Classification Based on Regency/City in West Nusa Tenggara Province

From Figure 4, it is evident that there is no difference in the classification of men's mean years of schooling at the beginning of the period, at the end of the period, or on average. There has been an increase in the average years of schooling, where in 2011, the low classification was in the range of 5.5-6 years, while in 2022, the low classification was in the range of 6.94-7.51 years. The majority of the regions in Lombok Island were classified as areas with low man mean years of schooling, except for Mataram City. Meanwhile, the majority of the regions in Sumbawa Island were classified in the moderate classification. Figure 5 illustrates a pattern of women's mean years of schooling that is similar to men's. The majority of regencies in Lombok Island were classified as areas with low women's mean years of schooling, while most regencies in Sumbawa Island were classified as areas with a moderate classification. Furthermore, Bima City, both at the beginning and end of the period, as well as on average, was classified as a region with the highest women's mean years of schooling. The difference in the range between the beginning and end of the period indicates an increase in the mean years of schooling in the West Nusa Tenggara.

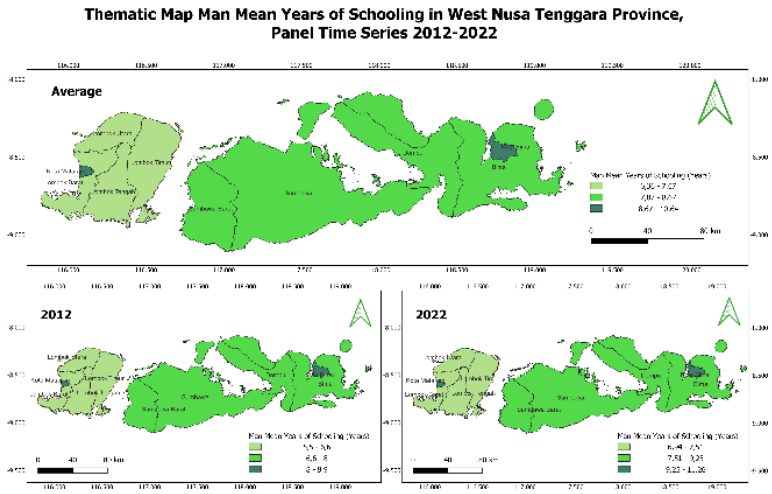

Figure 4: Men's Mean Years of Schooling Classification Based on Regency/City in West Nusa Tenggara Province

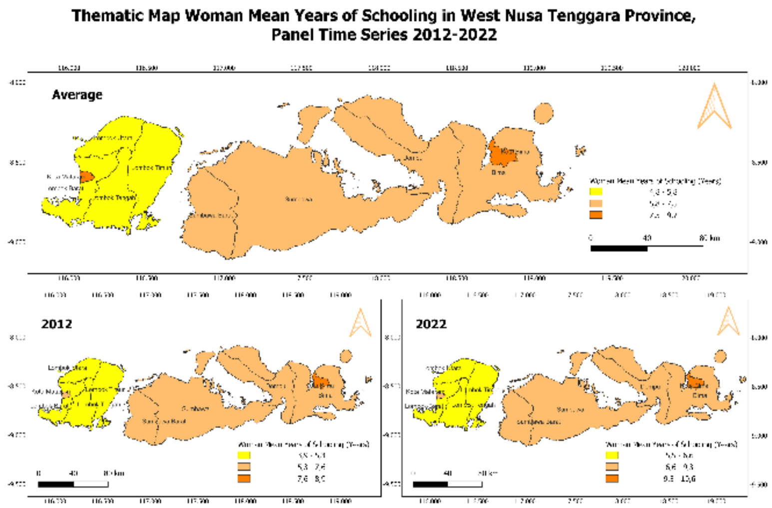

Figure 5: Women's Mean Years of Schooling Classification Based on Regency/City in West Nusa Tenggara Province

Based on Figure 6, it is consistently seen that the West Sumbawa region has the highest GRDP per capita value, whereas the urban areas consistently fall into the moderate classification. Changes occurred in the regions of West Lombok, North Lombok, and Bima Regency, where at the beginning of the period, they were classified as regions with moderate GRDP per capita, while at the end of the period, they were classified as regions with low

GRDP per capita. However, the values in each classification range at the beginning and end of the time significantly increased more than twofold compared to the beginning of the period. This indicates an uneven distribution of economic growth across the regencies/cities, mostly caused by income inequality (Kartiasih, 2019b; Kartiasih et al., 2023; 2023a; 2023b; Solihin et al., 2021). The distribution percentage of people living in poverty in West Nusa Tenggara Province shows consistent regional classifications at the beginning, end, and on average, as shown in Figure 7. The North Lombok region is classified as an area with the highest percentage of people living in poverty, indicating a significant gap in percentage compared to other regions. Further attention needs to be given to North Lombok due to its high percentage of poor population, which has an impact on the limited access to healthy foods and adequate healthcare facilities (Asri et al., 2023; Harum et al., 2023; Putri et al., 2023; Widyastuti et al., 2023; Kustanto, 2021). The government needs to seek solutions to the issues of economic growth and poverty since they can lead to a high incidence of infant mortality in West Nusa Tenggara.

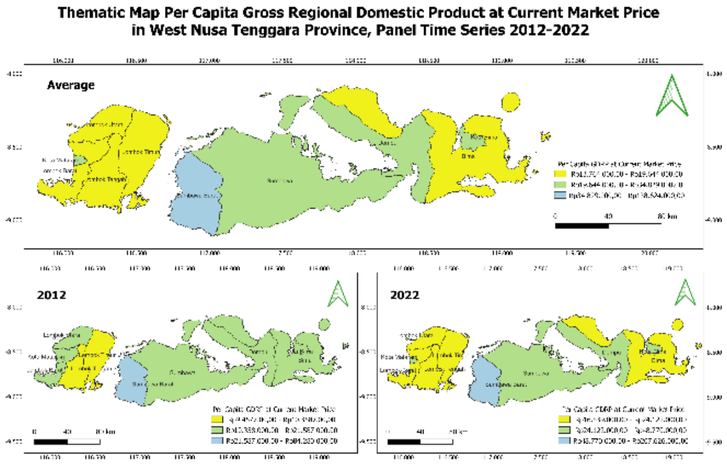

Figure 6: GRDP Per Capita Classification Based on Regency/City in West Nusa Tenggara Province

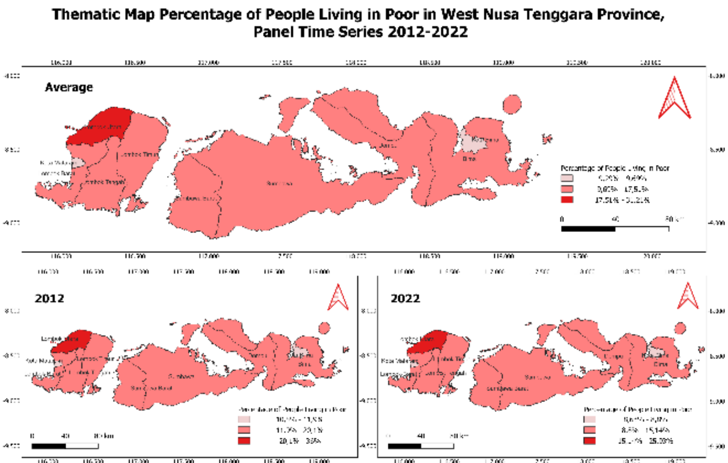

Figure 7: Percentage of People Living in Poverty Classification Based on Regency/City in West Nusa Tenggara Province

Figure 8 demonstrates that Mataram City consistently belongs to the category of regions with a high percentage of women working full-time, both at the beginning and end of the period, as well as on average. This indicates an active contribution of women to household economic activities. Bima Regency exhibits a distinct pattern, where both at the beginning and end of the period, it was classified as a region with a moderate percentage of women working full-time, although on average it belongs to the low classification. There were no significant fluctuations in the range values during the initial and final stages of this study. However, there was a 4.7% rise in the lower threshold of the low classification between 2012 and 2022. This indicates the smallest increase in the proportion of women employed full-time. Meanwhile, Figure 9 demonstrates that urban areas exhibit significantly higher women life expectancy at birth, both at the beginning and end of the period, as well as on average. West Lombok had a change in classification from low to moderate at the end of the period. This indicates an increase in women's life expectancy at birth during the past 11 years. The depiction of life expectancy is significant as it has an impact on reducing infant mortality (Cruz & Ahmed, 2018).

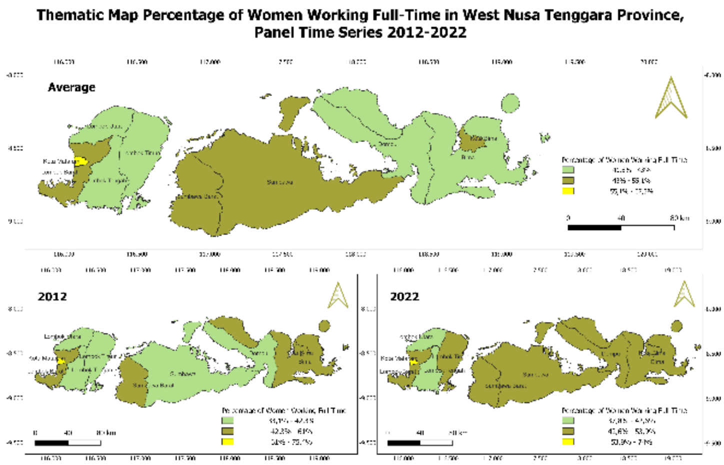

Figure 8: Percentage of Women Working Full-Time Classification Based on Regency/City in West Nusa Tenggara Province

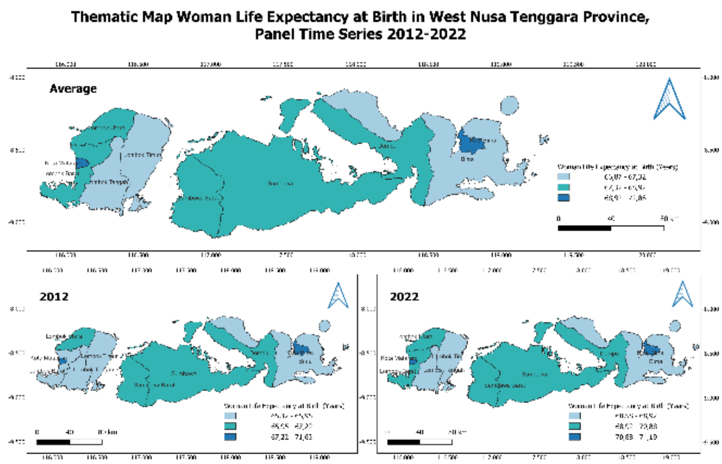

Figure 9: Women Life Expectancy at Birth Classification Based on Regency/City in West Nusa Tenggara Province

Long-term and Short-term Relationship and Causality between Variables

In the panel VECM analysis, the interrelationships between variables were first examined through their correlation values to determine the presence of multicollinearity. The purpose of conducting a multicollinearity check is to avoid the presence of strongly correlated variables that can affect the accuracy of research findings (Weaving et al., 2019). Prior to constructing the VECM model, Kousar et al. (2021) conducted multicollinearity testing. The Pearson correlation coefficient has a significant probability of multicollinearity when its value exceeds 0.8 (Shrestha, 2020). Based on Figure 10, it can be seen that there is a strong correlation between lnMYSMan and lnMYSWom at 0.98. Therefore, the research proceeded by including only the lnMYSWom variable in order to eliminate the risk of multicollinearity. This selection is based on the central role of mothers in childcare that can be directly applied to nurturing (Currie & Goodman, 2020).

When conducting panel data analysis, it is quite likely that the data would exhibit cross-sectional dependence, which might lead to biased estimations (Shabir et al., 2022). The Breusch-Pagan LM test yielded a p-value of 1, whereas the Pesaran-CD test yielded a p-value of 0.7891. This indicates that there is no spatial correlation in the variables used. Subsequently, a unit root test was conducted to examine the stationarity of the variables in order to avoid spurious regression. The testing of the panel VECM requires that the variables used in the study must be jointly stationary in the first difference (Hawari & Kartiasih, 2017; Ningsih & Kartiasih, 2019). The test results are shown in Table 2.

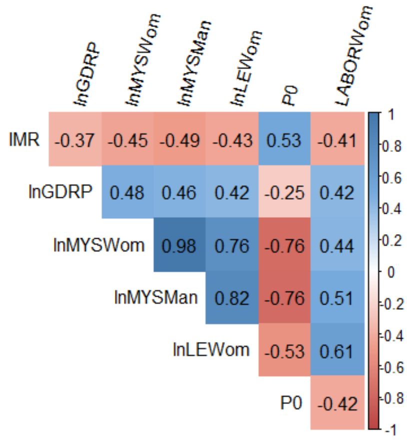

Figure 10: Correlation Coefficient Between Variables

Table 2: Unit Roots Test Results

Variable	Level (p-value)		First Difference (p-value)		Summary	
	ADF	PP	ADF	PP	ADF Test	Philips Peron Test
IMR	0.0003	0.0000	0.0000	0.0000	I(0) dan I(1)	I(0) dan I(1)
lnGRDP	1.0000	1.0000	0.0242	0.0000	I(1)	I(1)
lnMYSWom	0.0167	0.1131	0.0018	0.0002	I(0) dan I(1)	I(1)
lnLEWom	0.0046	0.0004	0.0007	0.0005	I(0) dan I(1)	I(0) dan I(1)
P0	0.8519	0.8132	0.0000	0.0000	I(1)	I(1)
LABORWom	0.0000	0.0009	0.0000	0.0000	I(0) dan I(1)	I(0) dan I(1)

The panel VAR approach requires testing for the optimum lag in order to provide satisfactory prediction results. Data processing using LR, FPE, AIC, SC, and HQ criteria shows that three out of five criteria recommend two as the optimum lag. Based on these results, the authors subsequently conducted a panel VAR verification using level data and found that the generated VAR model demonstrates stability, as there are no modulus values over one. In order to confirm that two is the optimum lag value, the authors performed a panel VAR stability test using a lag value that is one point higher for the endogenous variable. The results indicate that with a lag interval of three, the obtained panel VAR model remains stable, as shown in Table 3.

The study used non-stationary variables to search for the optimum lag. Therefore, for cointegration testing and the formation of the panel VECM model, a lag of (p-1) or in this case, lag two, was used. The use of this lag can be seen as an indication that the variables in the model are related to the current period and the period two years before. Furthermore, cointegration testing was conducted to see whether the panel VECM model can be applied to explain the model. Table 4 indicates that at a significance level of 5% based on the Maximum Eigenvalue, there are two cointegrations.

Table 3: VAR Stability Test Results

Root	Modulus
0.999871 - 0.003559i	0.999877
0.999871 + 0.003559i	0.999877
0.972316	0.972316
0.955741	0.955741
0.819416	0.819416
-0.339804 + 0.729604i	0.804853
-0.339804 - 0.729604i	0.804853
-0.260946 + 0.608047i	0.661675
-0.260946 - 0.608047i	0.661675
0.539474 - 0.245871i	0.592861
0.539474 + 0.245871i	0.592861
-0.576264	0.576264
0.288445 + 0.449122i	0.533770
0.288445 - 0.449122i	0.533770
-0.099645 + 0.474194i	0.484550
-0.099645 - 0.474194i	0.484550
-0.154052 + 0.263492i	0.305221
-0.154052 - 0.263492i	0.305221

Table 4: Panel Cointegration Test Results

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Probability
None *	0.469978	44.43857	40.07757	0.0151
At most 1 *	0.411364	37.09635	33.87687	0.0199
At most 2	0.276240	22.63066	27.58434	0.1898
At most 3	0.092317	6.780231	21.13162	0.9620
At most 4	0.025140	1.782295	14.26460	0.9949
At most 5	0.002928	0.205274	3.841465	0.6505

Based on the cointegration test, it is evident that there is a long-term cointegration among the research variables. This is supported by the significant negative coefficient value of -0.2266 in the formed panel VECM model system. The long-term model of the Panel VECM can be observed in Equations 6 and 7.

$$\begin{aligned} ECT1_{t-1} = {} & 1149.36 + 1.00IMR_{t-1} + 12.67\ln MYSWom_{t-1} - 287.12\ln LEWom^{**}_{t-1} \\ & - 0.25P0_{t-1} + 0.75LABORWom^{**}_{t-1} \end{aligned} \tag{11}$$

$$\begin{aligned} ECT2_{t-1} = {} & 249.96 + 1.00\ln GDRP_{t-1} + 1.86\ln MYSWom_{t-1} - 64.25\ln LEWom^{**}_{t-1} \\ & - 0.07P0_{t-1} + 0.15LABORWom^{**}_{t-1} \end{aligned} \tag{12}$$

**: Significant level at 5%.

The two long-term models demonstrate a significant correlation between women's life expectancy and infant mortality, as well as between the percentage of women working full-time and infant mortality. This is consistent with the research conducted by Rahman and Alam (2023), which found that the life expectancy of women had a significant negative impact on infant mortality rate. The first long-term equation indicates that a one percent increase in women's life expectancy in a previous period will result in a decrease of 2.8712 in the infant mortality rate (IMR) in the same period. Meanwhile, the IMR will decrease by 0.6425 for every one percent increase in women's life expectancy in the second equation. The negative relationship between the LEWom variable and IMR indicates that health factors are crucial in influencing infant health. The woman's life expectancy score reflects the government's ability to improve the well-being and provide adequate healthcare facilities to its citizens. Improved healthcare facilities will increase life expectancy, thereby reducing infant mortality rates. In addition, the percentage of women working full-time shows a positive correlation which is consistent with the research conducted by Titaley et al. (2008), but contradicts the findings of recent studies conducted by Rahman & Alam (2023) and Asif et al. (2022), which indicate that an increased number of working mothers will reduce infant mortality rates. The significant positive relationship in this study indicates that every one percent increase in women working full-time in the previous period will result in a 0.75 increase in infant mortality rate in Equation 6 and a 0.15 increase in Equation 7. It is understood that this positive relationship can occur due to the fact that the majority of women's primary employment sectors in West Nusa Tenggara are agriculture and small-scale trade, which weakens a woman's ability to have control over childcare, contrary to the findings of Asif et al. (2022).

Furthermore, the short-term panel VECM model for infant mortality rate could be seen in equation 8.

$$\begin{aligned} \Delta IMR_t = {} & 2.03^{**} - 0.23ECT1^{**}_{t-1} + 0.34ECT2^{*}_{t-1} - 0.13\Delta IMR_{t-1} - 0.06\Delta IMR_{t-2} \\ & - 2.79\Delta\ln GDRP_{t-1} - 1.07\Delta\ln GDRP_{t-2} + 44.16\Delta\ln MYSWom^{**}_{t-1} \\ & - 26.25\Delta\ln MYSWom^{*}_{t-2} - 164.25\Delta\ln LEWom_{t-1} \\ & - 320\Delta\ln LEWom^{*}_{t-2} + 0.04\Delta P0_{t-1} + 0.67\Delta P0_{t-2} \\ & + 0.05\Delta LABORWom_{t-1} - 0.05\Delta LABORWom^{*}_{t-2} \end{aligned} \tag{13}$$

**, *: significance level at 5% and 10%, respectively.

The short-term equation demonstrates a significant relationship between both long-term models, women's mean years of schooling in the previous period and two-year period, women's life expectancy in the previous two-year period, and the percentage of women working full-time in the previous one-year period, with infant mortality rate. The first-order cointegration is negatively associated with the short-term equation, where every increase of one first-order cointegration will decrease the infant mortality rate by 0.23. Meanwhile, the second cointegration is positively associated with the short-term model, where every increase of one second-order cointegration will increase the infant mortality rate by 0.34. Every one percent increase in women's mean years of schooling in a previous period will increase the infant mortality rate by 0.4416%. However, in the two previous periods, the infant mortality rate will decrease by 0.2625 for every one percent increase in women's mean years of schooling. The inconsistency leads to ambiguous outcomes in the short-term relationship, where there is a contradictory relationship between IMR and MYSWom in the previous year and two years prior. These findings contradict other studies that show both maternal and paternal education have a negative correlation with reducing infant mortality rates (Erdoğan et al., 2013; Schellekens, 2021).

The life expectancy of women in the two previous periods is significantly associated with the infant mortality rate at a 10% level of significance, where each one percent increase will decrease the IMR by 3.2. This is consistent with previous research indicating that regions with high life expectancy will have low infant mortality rates (Rahman & Alam, 2023; Wang & Ren, 2019). A high life expectancy indicates the presence of adequate healthcare facilities for the population, which effectively reduces infant mortality rates. Meanwhile, the percentage of women working full-time in the two previous periods is significantly associated with infant mortality, where each one percent increase will decrease the infant mortality rate by 0.07. The results indicate the presence of differential effects exerted by the LABORWom variable on IMR in the long and short term. The short-term outcomes are consistent with previous research indicating that women who work can reduce infant mortality rates (Asif et al., 2022; Rahman & Alam, 2023). In short-term, a working mother has control over her household affairs, allowing her to provide adequate nutrition and access to proper healthcare for her child. However, this power cannot be obtained by the mother in the long term.

Table 5: Granger Causality Test Results

Null Hypothesis	Obs.	F-Statistic	Prob.	Relation
lnGRDP does not Granger Cause IMR	80	0.16834	0.9174	No causality
IMR does not Granger Cause lnGRDP		0.46697	0.7062	
lnMYSWom does not Granger Cause IMR	80	3.76400	0.0143	lnMYSWom → IMR
IMR does not Granger Cause lnMYSWom		0.59201	0.6222	(unidirectional causality)
lnLEWom does not Granger Cause IMR	80	1.45471	0.2340	No causality
IMR does not Granger Cause lnLEWom		0.70948	0.5494	
P0 does not Granger Cause IMR	80	3.06464	0.0333	P0 → IMR
IMR does not Granger Cause P0		0.68047	0.5668	(unidirectional causality)
LABORWom does not Granger Cause IMR	80	1.11644	0.3481	No causality
IMR does not Granger Cause LABORWom		0.71224	0.5478	

The results of the model's feasibility test indicate that the adjusted R-squared value is 0.35, which suggests that the variables included have a sufficiently strong effect (Hair et al., 2013). The Portmanteau Autocorrelation Coefficient residual test indicates that for all lag values, the probability is greater than 0.05, indicating that there is no residual autocorrelation in the model. Meanwhile, the white heteroskedasticity test indicates a p-value of 0.3139, which fails to reject the null hypothesis, indicating that the residual variances are homogeneous. The test for residual normality on the AKB variable as the response variable shows a p-value of 0.9464 for the Jarque-Bera test, indicating that the residuals are normally distributed.

The analysis continued by observing the Granger causality relationship. Saputra &

Sukmawati (2021) identified that a causal relationship exists when the obtained p-value is less than 0.05. Based on Table 5, it can be observed that there is a unidirectional causal relationship between the natural logarithm of women's mean years of schooling and infant mortality rate as well as between the percentage of people living in poverty and infant mortality rate.

The Impulse Response analysis was conducted to examine how an endogenous variable can influence other endogenous variables and increase the reliability of econometric VAR models. The impulse response function indicates a positive influence and vice versa (Batubara & Saskara, 2015). The results in Figure 11 visually demonstrate the response of the IMR variable to a one-standard deviation shock, both from itself and from other variables, across a 50-period horizon. The IMR response clearly indicates fluctuations at the beginning of the period, followed by reaching its equilibrium point where most variables have stabilized by the 20th period.

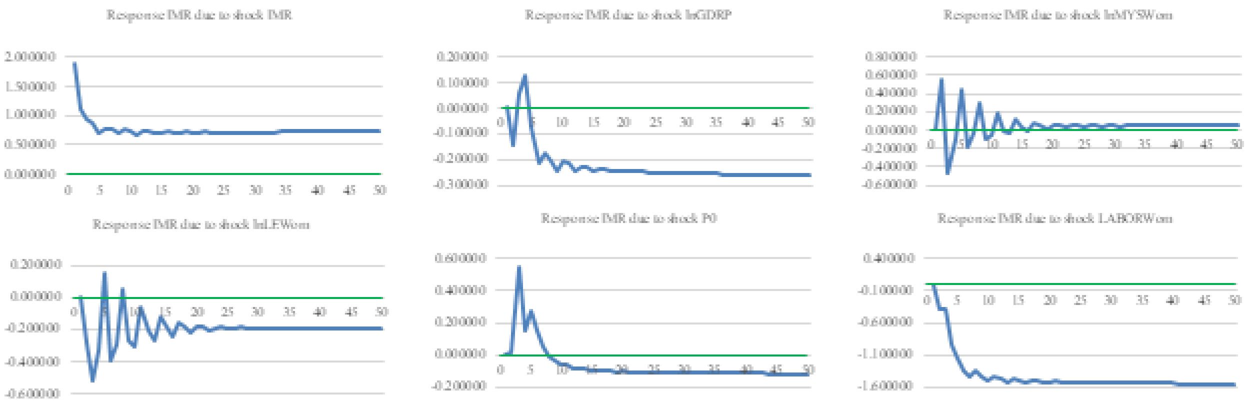

Figure 11: The Impulse Response of IMR to Shocks Caused by Research Variables

An increase in one-standard deviation in the initial Shock IMR resulted in a subsequent 1.84% increase, followed by a decline in the second year, eventually stabilizing by the twentieth year. The negative trend with a positive response indicates that the IMR's response to its own shock is generally weak. Meanwhile, the GRDP per capita shock in the first period did not elicit any response from IMR, but in the second year it showed a decline of 0.14. During the fifth period, there was a noticeable negative trend with negative types of responses. Under stable conditions, a shock of one-standard deviation from the lnGRDP value will elicit a negative response from the IMR. The IMR response to the Women's Mean Years of Schooling shock indicates a fluctuating positive response followed by stability in the 30th period. The positive response provided is inconsistent with research indicating that female education has a negative correlation with infant mortality (Rahman & Alam, 2023).

The life expectancy of women did not show any fluctuations in the first period, but in the second year it responded with a decrease at 0.27 and reached its lowest point in the third period. During the 25th period, IMR response to the shock in women's life expectancy began to exhibit stability with a negative response that is consistent with previous research (Rahman & Alam, 2023). The response of IMR towards the shock in the number of people living in poverty began in the second period with an increase at 0.027 and reached its peak increase in the third period, followed by a significant decline. The IRF for IMR due to P0 shock exhibits a response consistent with the findings of Taylor-Robinson et al. (2019) during the first seven periods. However, subsequent results indicate a contrary negative response compared to previous research. The shock from the percentage of women working full-time began in the second period with a decrease at 0.37, followed by a significant decrease in the fourth period at 0.94. The response provided by IMR indicates that a shock of one-standard deviation in the percentage of women working full-time will have a negative impact on infant mortality rates, which is consistent with the findings of Asif et al. (2022) and remains stable until the 25th period.

Figure 12 shows a visualization of the proportion of Forecast Error Variance Decomposition for IMR for the next fifteen periods. Variance Decomposition analysis is used to quantify the degree to which a variable influences the system, allowing the identification of variances within the established model (Batubara & Saskara, 2015). It is evident that during the second period (short term), self-inflicted shocks still result in the highest proportion of fluctuations in infant mortality rate. Therefore, short-term fluctuations are still influenced by the IMR variable itself. However, in the long term, the self-contribution to fluctuations gradually decreases, while the fluctuations caused by other variable shocks increase. Even in the ninth period, the contribution of fluctuations caused by IMR shocks is smaller compared to the contribution of shocks in the percentage of women working full time. This indicates that the composition of fluctuations in the ninth period consists of 42.36% IMR, 1.03% lnGRDP, 3.96% lnMYSWom, 3.72% lnLEWom, 1.98% P0, and 46.94% LABORWom. From the proportions obtained, it is evident that the decrease in the contribution of IMR shocks to fluctuations and the increase in the contribution of other variables are quite significant.

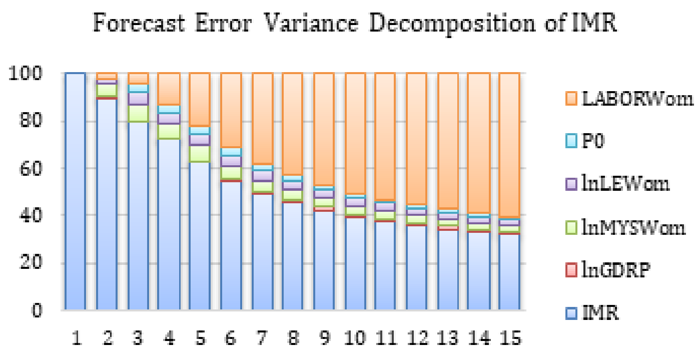

Figure 12: Forecast Error Variance Decomposition of IMR

Conclusion

Reducing infant mortality has become a mandatory goal that is implemented both internationally and nationally, especially in Indonesia as a developing country. West Nusa Tenggara Province was selected as the research site due to its high infant mortality rate as well as its inequality and gender inequality indices, making it suitable for examining the socioeconomic factors and female indicators that influence infant mortality. This study classified the regions into three groups based on the early period, late period, and average period. Long-term testing reveals the presence of two cointegrations with a significant negative relationship between women's life expectancy at birth and IMR, as well as a significant positive relationship between the percentage of women working full-time and IMR. In the short-term relationship, the first cointegration in the previous period, the women's mean years of schooling in the two previous periods, the women's life expectancy at birth in the two previous periods, and the percentage of women working full time in the two previous periods are all significantly negatively correlated with the IMR in the current period. Meanwhile, the second cointegration in the previous period and the women's mean years of schooling in the previous period are positively associated with the infant mortality rate in the current period.

This study also identified the presence of unidirectional causality between women's mean years of schooling and the number of people living in poverty and IMR. Based on the results of this study, it is expected that the Government of West Nusa Tenggara Province will be able to provide equal access and learning opportunities for women living in the region. Additionally, women's empowerment should be supported through equal work opportunities and fair access to healthcare facilities. Finally, regional investment should be increased in order to enhance economic growth.

This study still has limitations, including the limited infant mortality data obtained solely based on reported deaths, which carries a significant potential for bias. The authors focused only on utilizing socio-economic factors and female indicators. Furthermore, the authors fail to consider the health indicators and high rates of child marriage in West Nusa Tenggara and its impact on infant mortality, as evidenced from Paul (2020) who demonstrates a significant correlation. Therefore, this study can be further developed by including health factors and the number of child marriages in the West Nusa Tenggara as explanatory variables.

Declaration

Conflict of Interest

This research was conducted without any potential biases or conflicts of interest that could have compromised the reliability and validity of the findings.

Availability of Data and Materials

This study utilized secondary data obtained from the BPS-Statistics Indonesia and the Public Health Office of West Nusa Tenggara for analysis. This article also includes a shapefile provided by the Indonesia Geospatial Information Agency.

Funding Source

This study is funded at the authors' own cost.

Acknowledgment

The authors would like to express their gratitude to the reviewers for their valuable feedback which contributed to improving this article.

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