MODELING AND FORECASTING OF SOCIOECONOMIC MORTALITY DIFFERENTIALS ACROSS SUBPOPULATIONS IN THAILAND

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ABSTRACT

This research aims to investigate the associations between mortality rates and socioeconomic status across various subpopulations in Thailand, with a specific focus on average income as represented by GPP per capita. The analysis utilizes the Lee-Carter model and its extensions for modeling and forecasting mortality rates. Furthermore, it evaluates the effectiveness of these models and applies the findings to relevant scenarios, particularly in the context of life insurance. The results indicate that the augmented common factor model is the most appropriate for modeling and forecasting socioeconomic mortality differentials among both male and female subpopulations. Moreover, socioeconomic status significantly influences mortality rates across various subpopulations in Thailand. The findings reveal that older individuals in high GPP per capita groups, specifically those aged 70 and above for males and 60 and above for females, experience the lowest mortality rates compared to other subgroups. In contrast, certain age ranges within low GPP per capita subpopulations—males approximately 12 to 65 years old and females approximately 13 to 57 years old—exhibit the lowest mortality rates relative to other subgroups. These differential mortality rates significantly affect the variability of life insurance benefits.

Keywords: Mortality, Socioeconomic Status, Modeling, Forecasting, Lee-Carter Model

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INTRODUCTION

Mortality rates within any country typically exhibit significant variations among subpopulations defined by factors such as demographics, geography, health-related characteristics, and socioeconomic status. Among these determinants, socioeconomic status profoundly impacts mortality rates, encompassing dimensions such as income, education, and occupation. Numerous studies have consistently demonstrated a robust inverse association, indicating that higher socioeconomic groups tended to experience lower mortality rates compared to those in lower socioeconomic groups (Townsend & Davidson, 2014).

These socioeconomic mortality differentials among subgroups significantly influence various aspects, including the design of public policies and the redistribution properties of defined benefit and defined contribution pension schemes (Friedberg, 2000; Liebman, 2002). Furthermore, these differentials impact the pricing of insurance products and insurers' management of mortality and longevity risk.

The challenges arising from variations in socioeconomic mortality rates offer valuable opportunities for research and application, particularly in the context of Thailand, where income inequalities are prevalent. The World Bank (2021) substantiated this assertion, reporting that Thailand's Gini coefficient stands at 43.3 percent—the highest in the East Asia and Pacific region—thereby underscoring a skewed income distribution characterized by a substantial concentration of wealth within a relatively small segment of the population. Consequently, income inequality emerges as a crucial driver of socioeconomic challenges, fundamentally associated with varying income levels.

Income plays a vital role as a socioeconomic status, influencing diverse mortality rates across different subpopulations in Thailand. Research by Deaton and Paxson (1998) supported this notion, providing robust evidence that financial constraints often impeded lower-income groups' access to essential healthcare services, leading to poorer health outcomes and higher mortality rates. Moreover, Bayati et al. (2013) underscored the importance of income as a fundamental socioeconomic determinant of health, profoundly impacting overall well-being. Additionally, the perspectives of Adler et al. (1994) collectively encouraged the correlation between improved health outcomes across the entire income distribution and increased income.

To measure income as an indicator of socioeconomic status, researchers often refer to metrics such as Gross Domestic Product (GDP) per capita. Higher GDP per capita was associated with improved national living standards and economic development (Stengos et al., 2008; Ediev, 2011), which correlated with elevated socioeconomic status. Moreover, higher GDP per capita was linked to better health outcomes and lower mortality rates (Stengos et al., 2008; Mpofu, 2013). Nonetheless, GDP per capita has limitations when analyzing socioeconomic mortality differentials, as it reflects economic output per person at the national level. Hence, utilizing subnational indicators is crucial for enhanced analytical precision. Gross Provincial Product (GPP) per capita, which is similar to GDP per capita, provides insights into economic output within specific provinces. By employing GPP per capita as an appropriate metric, researchers can conduct a more focused analysis of the relationship between income, as an indicator of socioeconomic status, and mortality rates across various subpopulations.

Therefore, this requires not only the selection of appropriate economic indicators but also the use of methods that can effectively assess and analyze socioeconomic mortality differentials, enabling the simultaneous modeling of mortality in multiple subpopulations. Some studies use traditional statistical methods like regression analysis (Mackenbach et al., 2016) and survival analysis (Richards, 2008) to evaluate mortality differentials. These approaches neglect the mortality improvements associated with socioeconomic profiles and the future. Nonetheless, several studies have sought to address these limitations, thereby enhancing our understanding of the dynamics underlying socioeconomic mortality differentials. Incorporating time-varying covariates into analytical methods presents a promising approach for exploring these differentials within subgroups, particularly through the multiple population extensions of the Lee-Carter, which account for mortality improvements (Villegas & Haberman, 2014).

This research aims to investigate the associations between mortality rates and socioeconomic status across various subpopulations in Thailand, specifically focusing on average income as represented by GPP per capita. The analysis utilizes the Lee-Carter model and its extensions for modeling and forecasting. Additionally, the study explores the effectiveness of these models and applies the findings to scenarios, particularly in the context of life insurance.

LITERATURE REVIEWS

Relationship between Socioeconomic Status and Mortality Rates

The literature reviews are limited to the income dimension and its related components, as this research primarily seeks to evaluate socioeconomic status within this framework, with a particular focus on certain subpopulations. The study by Jusot (2006) investigated the relationship between income and health status, focusing particularly on the most impoverished segments of the population through survival models. The findings indicate that individuals with lower incomes experience a higher probability of mortality, thereby highlighting the substantial influence of income on health outcomes. Similarly, Po and Subramanian (2011) explored the effects of social castes and income on mortality rates in India using logistic regression, revealing that those in the lowest income and asset quintiles face an elevated risk of death. Numerous studies, both international and national, support this notion, including Hoffmann (2005) with frailty models and Nirarat and Kidsom (2017) employing multiple regression analysis. Overall, these studies consistently show that among the analyzed subpopulations, lower-income groups have higher mortality rates than their higher-income counterparts.

The Comparative Effectiveness of an Independent Model versus Multiple Joint Models of the Lee-Carter Model within a Multi-population Mortality Framework

To begin, Li and Lee (2005) extended the Lee-Carter model (Lee & Carter, 1992) to simulate mortality across multiple populations, utilizing joint modeling to impose parameter structures that prevent divergence in mortality forecasts over time. The authors anticipated populations with close ties—such as geographic proximity or similar economic conditions—to exhibit comparable mortality patterns. Later, Li and Hardy (2011) compared the independent Lee-Carter model with four joint models. The results showed that the augmented common factor model offered the best goodness-of-fit and forecasting accuracy. Moreover, Nor et al. (2018) applied multi-population mortality models to examine population relationships. The results showed that the augmented common factor model outperformed the independent model in terms of historical fit and forecast accuracy. Eriksson (2020) found that joint models consistently did better than independent models across all forecast periods. Therefore, these studies highlight the critical role of joint modeling in enhancing mortality fitting and forecasting reliability. They suggest significant correlations among the examined subpopulations and underscore the importance of considering shared mortality patterns in modeling approaches.

RESEARCH METHODOLOGY

Source of Data Collection

This study used secondary data from various government organizations.

(i) Provincial population data (by gender and age) span 2002-2022. (ii) Provincial mortality data (by gender and age) span 2003-2022. (iii) Real Gross Provincial Product data (chain volume) span 2017-2021. In this research, we estimate the parameters of all models using in-sample data spanning 2003-2018 and test their accuracy with out-of-sample data from 2019-2022. Note: (i) and (ii) were collected from the Bureau of Registration Administration, Department of Provincial Administration, Ministry of Interior, Thailand; and (iii) from the Office of the National Economic and Social Development Council, Thailand.

Grouping

Upon collecting the data, we first determined the Real GPP per capita for the period spanning 2017-2021 and subsequently projected its value in 2023. Subsequently, we employed a weighted average approach to calculate the Real GPP per capita for 2023. Finally, the weighted average Real GPP per capita for 2023 was organized in ascending order. Based on the sorted values, classifications were established as follows: the lowest 20th percentile was categorized as low GPP per capita, the 21st to 80th percentiles were designated as medium GPP per capita, and values above the 80th percentile were classified as high GPP per capita. Following this grouping, the next step involved data preparation, followed by the modeling process.

Modeling Socioeconomic Mortality Differentials

The Lee-Carter model and its extensions presented in this study propose a parametric representation where ${}_nm_{x,t}^{(i)}$ denotes the central death rate for people age $]x, x+n($ in subpopulation i during year t, calculated as

$${}_nm_{x,t}^{(i)} = {}_nD_{x,t}^{(i)} / {}_nL_{x,t}^{(i)} \quad (1)$$

where ${}_nD_{x,t}^{(i)}$ is the number of deaths at age $]x, x+n($ in subpopulation i during year t and ${}_nL_{x,t}^{(i)}$ is the mid-year population estimate for age $]x, x+n($ in subpopulation i during year t. Let age $x \in X := \{x_1, x_2, .., x_k\}$, year $t \in T := \{t_1, t_2, .., t_n\}$, and subpopulation $i \in I := \{i_1, i_2, .., i_m\}$.

The Lee-Carter Model

The simplest approach to modeling mortality in subpopulations is to apply the Lee-Carter model, as proposed by Lee and Carter (1992), to each one. The model is expressed as:

$$\ln {}_nm_{x,t}^{(i)} = a_x^{(i)} + b_x^{(i)} k_t^{(i)} + \varepsilon_{x,t}^{(i)}, \ \varepsilon_{x,t}^{(i)} \sim N(0, \sigma_\varepsilon^{2^{(i)}}) \quad (2)$$

where $a_x^{(i)}$ describes age-specific parameter mortality level for the subpopulation i at age x, $b_x^{(i)}$ measures the age-specific parameter that reflects how the mortality rate at age *x* responds to changes in the overall level for subpopulation, $k_t^{(i)}$ serves as a time-varying mortality index representing the level of mortality improvement in year t for subpopulation i, $\varepsilon_{x,t}^{(i)}$ is the error term. With the constraints: $\sum_{x \in X} b_x^{(i)} = 1$ and $\sum_{t \in T} k_t^{(i)} = 0$

The Joint K-Model

An alternative for modeling mortality differentials is the joint K-model proposed by Lee and Carter (1992), which assumes that all populations are influenced by a single time-varying index.

The model is expressed by

$$\ln {}_nm_{x,t}^{(i)} = a_x^{(i)} + b_x^{(i)} k_t + \varepsilon_{x,t}^{(i)}, \ \varepsilon_{x,t}^{(i)} \sim N(0, \sigma_\varepsilon^{2^{(i)}}) \quad (3)$$

Where k_t denotes a time-varying mortality index across all subpopulations in year t.

With the constraints $\sum_{x \in X} b_x^{(i)} = 1$ and $\sum_{t \in T} k_t = 0$

The Common Factor Model

Li and Lee)2005 (propose an alternative approach that assumes all subpopulations experience the same mortality improvements at all times. The formula is:

$$\ln {}_nm_{x,t}^{(i)} = a_x^{(i)} + b_x k_t + \varepsilon_{x,t}^{(i)}, \ \varepsilon_{x,t}^{(i)} \sim N(0, \sigma_\varepsilon^{2^{(i)}}) \quad (4)$$

Where b_x measures the common age-to-period sensitivity at age x across all subpopulations. With the constraints: $\sum_{x \in X} b_x = 1$ and $\sum_{t \in T} k_t = 0$

The Augmented Common Factor Model

To enhance the common factor model, Li and Lee)2005(introduced a population-specific factor, defined as:

$\ln {}_{n}m_{x,t}^{(i)} = a_x^{(i)} + b_x k_t + b_x^{(i)} k_t^{(i)} + \varepsilon_{x,t}^{(i)}$, $\varepsilon_{x,t}^{(i)} \sim N(0, \sigma_\varepsilon^{2(i)})$ (5)

With the constraints $\sum_{x \in X} b_x = 1$, $\sum_{t \in T} k_t = 0$, $\sum_{x \in X} b_x^{(i)} = 1$ and $\sum_{t \in T} k_t^{(i)} = 0$

In this research, we use the maximum likelihood estimation (MLE) technique to estimate the parameters of the Lee-Carter model and its extensions. A fundamental assumption underlying our analysis is that the number of deaths follows a Poisson distribution. This assumption is significant, as it effectively mitigates the concerns related to the assumption of homoskedastic errors, as emphasized by Brouhns et al. (2002). Additionally, based on the acquired data, there is a tendency for the mortality rate to decline with advancing age. Prior to estimating the parameters of these models, the mortality rates for the elderly are graduated using the approach proposed by Coale and Kisker (1990). After completing the modeling process, the next step involves conducting forecasts. While the model demonstrates a good fit for the in-sample data, it may exhibit inadequate forecasting performance.

Forecasting

The ARIMA (p,d,q) time-series model is utilized to analyze the mortality index across subpopulations within all socioeconomic mortality differential models. In this research, a 10-year forecast is conducted to project future mortality trends

Model Selection

Model selection entails identifying the most suitable model by evaluating various criteria, such as goodness-of-fit tests and forecasting performance. Thus, in this research, we selected the most effective model by collectively considering all these criteria. After that, we will proceed to the discussion and application phase.

Life Insurance Application

In this section of the research, we aim to compute premiums using the most appropriate model for the socioeconomic subpopulation. Additionally, we will derive premiums without accounting for socioeconomic status, as well as premiums calculated from the TMO17 mortality table. We will then compare the resulting premiums to evaluate the differences.

Definition: A 10-year endowment insurance policy provides a 1,000 THB benefit payable at the end of the year of death if the policyholder dies within the 10-year term. If the policyholder is still living at maturity, a benefit payment of 1,000 THB is made at the end of the 10 years. This policy assumes a net single premium payment. The interest rate is 2%. Using the equivalence principle, the net premium is determined by:

Expected present value of premiums = Expected present value of benefits

Expected present value of premiums = Expected present value of death benefits + Expected present value of survival benefits

Statistical Measures

In evaluating the goodness of fit for various models, we utilize the Bayesian Information Criterion (BIC) as proposed by Cairns et al. (2009):

$BIC = L - 0.5\nu\log(N)$ (6)

Where L is the maximum log-likelihood of the model, ν is the effective number of parameters, and N refers to the total number of observations. According to this formulation, models exhibiting higher BIC values indicate a better balance between model fit and complexity.

The Root Mean Squared Error (RMSE) is a critical metric for assessing forecast accuracy. It is defined by the following equation:

$$RMSE = \sqrt{\sum_{i \in I} \sum_{t \in T} \sum_{x \in X} \frac{(\ln {}_{n}m_{x,t}^{(i)} - \ln {}_{n}\widehat{m}_{x,t}^{(i)})^2}{N}} \quad (7)$$

Where ${}_{n}m_{x,t}^{(i)}$ and ${}_{n}\widehat{m}_{x,t}^{(i)}$ represents the actual and predicted mortality rate, respectively, for age [x,x+n) in year t for subgroup i, N denotes the total number of observations, covering all ages, years, and subgroups. A smaller RMSE suggests that the predicted mortality rates align more closely with the observed rates, indicating greater model accuracy in forecasting the data.

RESEARCH RESULTS

Grouping

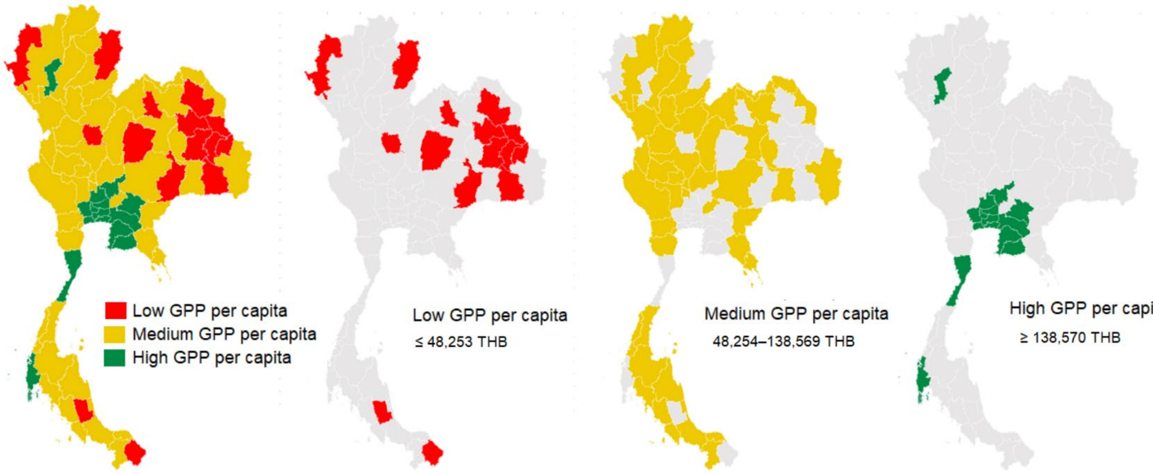

Figure 1 Grouping of Subpopulations Using the Weighted Average Real GPP Per Capita for 2023.

The findings illustrated in Figure 1 depict the grouping of subpopulations. The results indicate that the low GPP per capita group, marked by the red regions, is predominantly concentrated in northeastern Thailand. On the other hand, the high GPP per capita group, depicted by the green zones, is primarily situated in the Bangkok Metropolitan Region, along with industrial estates and tourist towns. The remaining areas are classified as medium GPP per capita.

Goodness-of-Fit in Modeling Socioeconomic Mortality Differentials

Table 1 Effective Number of Parameters (ν), Log-Likelihood (L), BIC Values for Various Models Applied to Male Subpopulations on In-Sample Data.

Model	ν	L	BIC
Lee-Carter	168	-9,444	-10,021(2)
Joint-K	176	-12,346	-13,093(3)
Common factor	116	-14,235	-14,634(4)
Augmented common factor	203	-7,863	-8,560(1)

Table 2 Effective Number of Parameters (ν), Log-Likelihood (L), BIC Values for Various Models Applied to Female Subpopulations on In-Sample Data.

Model	ν	L	BIC
Lee-Carter	168	-7,185	-7,762(2)
Joint-K	176	-8,652	-9,399(3)
Common factor	116	-9,414	-9,812(4)
Augmented common factor	203	-6,156	-6,853(1)

Tables 1 and 2 present the BIC values for each model applied to male and female subpopulations, along with their respective rankings indicated in brackets. The augmented common factor model consistently ranks first for both subpopulations. This indicates that it provides the best fit for the in-sample data and demonstrates a superior ability to explain socioeconomic mortality trends compared to the other models. Furthermore, the Lee-Carter model offers a moderate fit across both subpopulations, while the joint-K model and common factor model are less effective, particularly in their capacity to account for the complexities of mortality influenced by socioeconomic status.

Forecast Performance in Modeling Socioeconomic Mortality Differentials

Table 3 Root Mean Square Error (RMSE) of Log Central Death Rates for Various Models Applied to Male and Female Subpopulations on Out-of-Sample Data.

Model	RMSE of Male Subpopulations	RMSE of Female Subpopulations
Lee-Carter	0.1305(3)	0.1411(3)
Joint-K	0.1077(1)	0.1294(2)
Common factor	0.1348(4)	0.1634(4)
Augmented common factor	0.1089(2)	0.1209(1)

Table 3 demonstrates the RMSE values for each model applied to male and female subpopulations, with corresponding rankings indicated in brackets. In the male subpopulations, the joint-K model achieves the lowest RMSE, indicating that it provides the most accurate forecasts among the evaluated models. Conversely, for the female subpopulations, the augmented common factor model ranks highest, demonstrating its superior ability to predict mortality rates. Moreover, the Lee-Carter model exhibits moderate performance, ranking third for males and females. In contrast, the common factor model consistently exhibits the lowest performance across both subpopulations, suggesting that it may not be the most suitable choice for forecasting mortality rates in either group.

Model Selection

For female subpopulations, the augmented common factor model is the most appropriate, providing superior in-sample fit and predictive accuracy. For males, while the joint-κ model demonstrates better out-of-sample accuracy but poor fitting, the augmented common factor model exhibits stronger in-sample performance, with only a slightly higher RMSE in forecasting. Thus, overall, the augmented common factor model is the most suitable.

Results of Socioeconomic Mortality Differentials

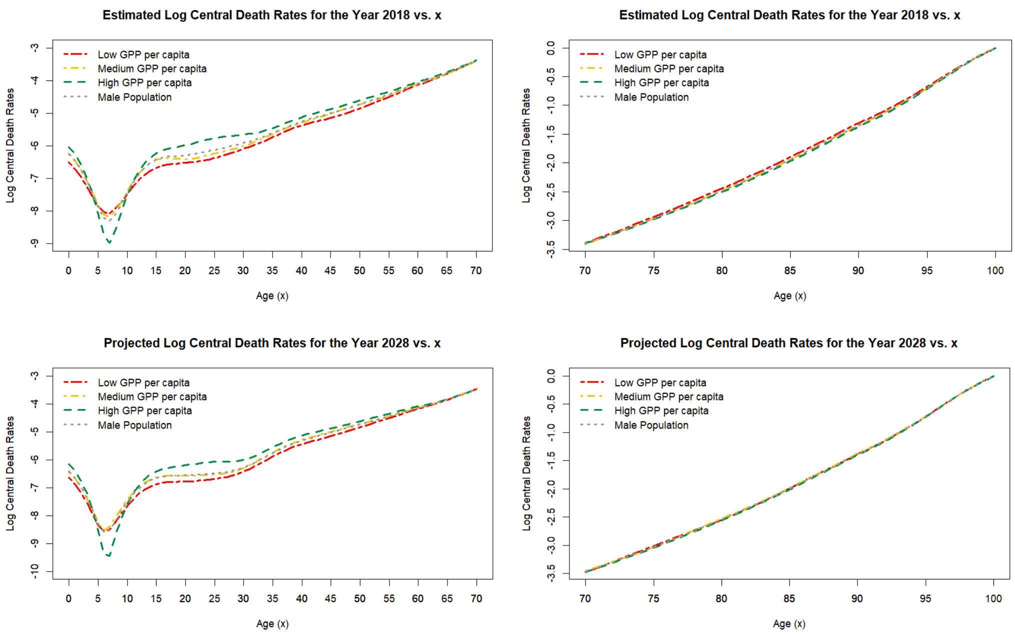

Figure 2 Estimated Log Central Death Rates in the Year 2018 and Projected Rates in the Year 2028 for Males at Age x.

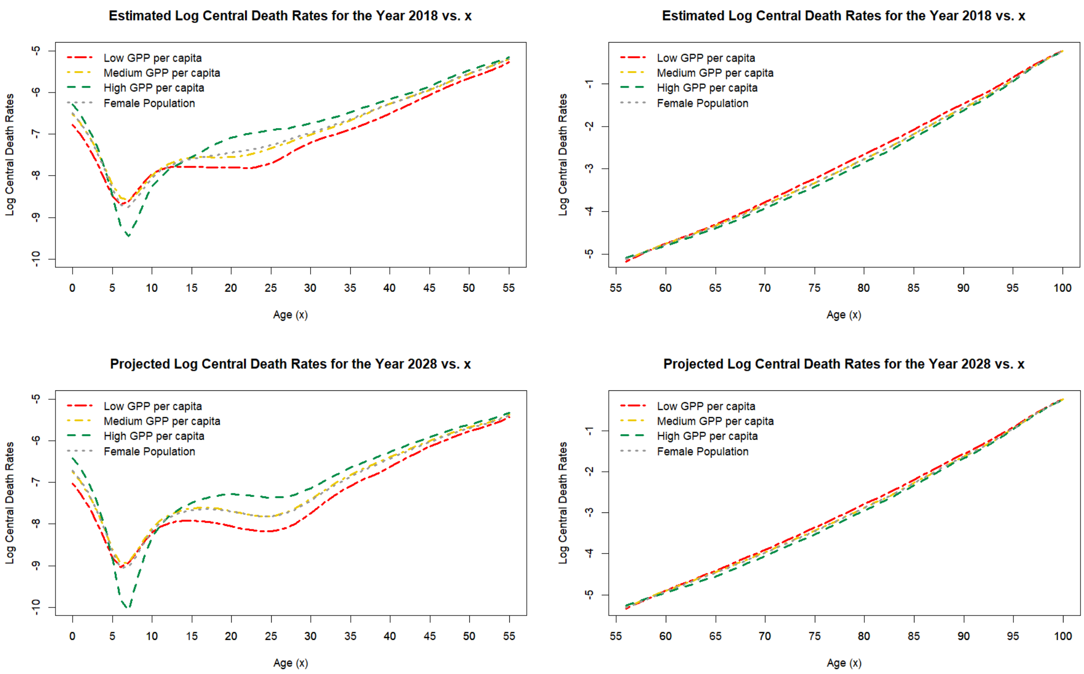

Figure 3 Estimated Log Central Death Rates in the Year 2018 and Projected Rates in the Year 2028 for Females at Age x.

In the analysis, Figures 2 and 3 illustrate the estimated log central death rates for males and females, respectively, in 2018 and the projected rates for 2028, as derived from the augmented common factor model. Both figures highlight the evolution of mortality rates across subgroups categorized by low, medium, and high GPP per capita, suggesting that age-specific mortality rates are projected to decline continuously while maintaining the prominent existing patterns of mortality differentials. Moreover, the findings in Figure 2 indicate that males aged approximately 12 to 65 in the low GPP per capita subgroups exhibit the lowest mortality rates, whereas those in the same age range in the high GPP per capita subgroup experience the highest mortality rates. Similarly, Figure 3 reveals that females aged approximately 13 to 57 in the low GPP per capita group display the lowest mortality rates, while those in the high GPP per capita subgroups demonstrate the highest rates for this age range. Conversely, for individuals aged approximately 70 and older among males and 60 and older among females, the trend reverses in both figures, with the low GPP per capita subgroups exhibiting the highest mortality rates while the high GPP per capita subgroups show the lowest rates. Furthermore, the mortality rates for all ages within the medium GPP per capita subgroups closely align with those observed in the overall male and female populations. In addition to these findings, the figures reveal that socioeconomic status impacts mortality rates differently across subpopulations, with notable deviations observed in both sexes within low GPP per capita subgroups compared to the overall population, as well as in high GPP per capita subgroups.

Life Insurance Application

In the analysis, Figure 4 presents the expected present value (EPV) of death benefits and survival benefits for males in 2018. The results indicate that the EPV of death benefits, which ranges from 0 to 80, increases steadily with age, while the EPV of survival benefits decreases over the same range. The research findings indicate that socioeconomic status significantly impacts mortality rates across subpopulations, leading to deviations in the EPV of death and survival benefits compared to the male population. Specifically, the figure illustrates that the low GPP per capita subgroups have a reduced EPV of death benefits and an elevated EPV of survival benefits for individuals aged 0 to 63 relative to the male population. In contrast, the high GPP per capita subgroups exhibit an increased EPV of death benefits and a diminished EPV of survival benefits in the age range of 6 to 66. Furthermore, a comparison of death benefits among GPP per capita subgroups and the entire male population with those derived from the Thai mortality table for ordinary business (TMO17) reveals that the TMO17 provides the lowest EPV of death benefits and the highest EPV of survival benefits in these age ranges. Nevertheless, this trend reverses for individuals aged 64 to 80, where the low GPP per capita subgroups display an increased EPV of death benefits and a diminished EPV of survival benefits compared to the male population. Conversely, the high GPP per capita subgroups present an elevated EPV of survival benefits alongside a reduced EPV of death benefits in the age range of 67 to 80. A similar comparison reveals that TMO17 provides the highest EPV of death benefits and the lowest EPV of survival benefits in these age ranges.

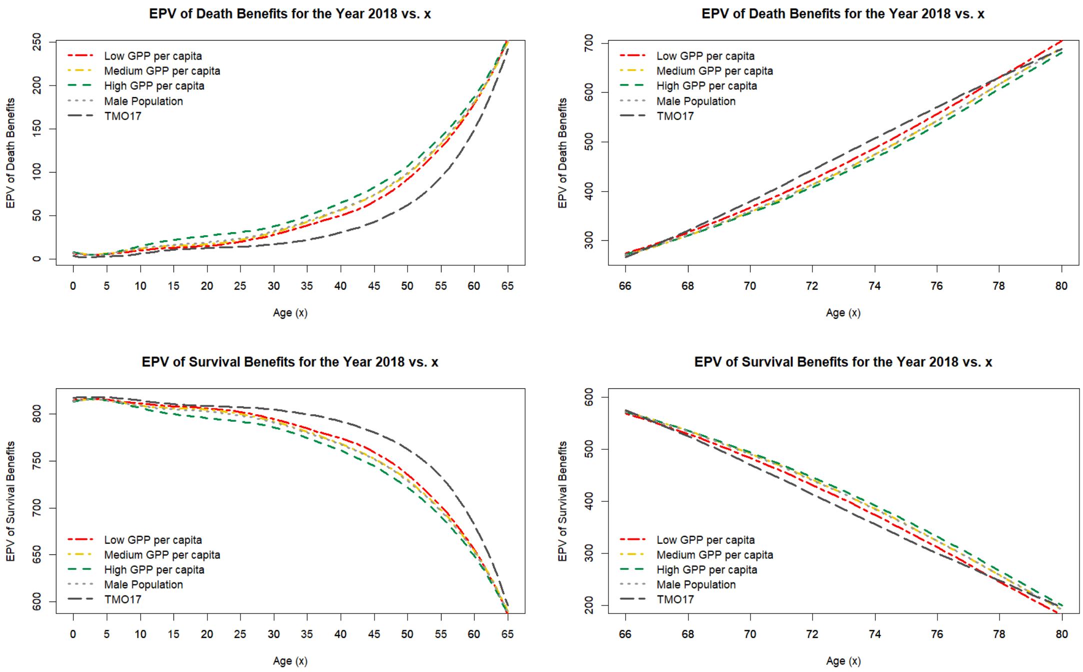

Figure 4 Expected Present Value of Death Benefits and Survival Benefits (in THB per 1,000 THB Sum Assured) for Males at Age x in the Year 2018.

In the analysis, Figure 5 illustrates the EPV of death and survival benefits for females in 2018. The findings reveal that the EPV of death benefits, which ranges from 0 to 80, consistently rises with age, whereas the EPV of survival benefits declines over the same age range, similar to the patterns observed in males. Furthermore, socioeconomic status significantly impacts mortality rates across subpopulations, resulting in deviations in the EPV of death and survival benefits for females that are analogous to those found in males. The low GPP per capita subgroups exhibit a lower EPV of death benefits and a higher EPV of survival benefits for individuals aged 0 to 53, compared to the overall female population. In contrast, the high GPP per capita subgroups show a higher EPV of death benefits and a lower EPV of survival benefits in the age range of 8 to 53. Moreover, when comparing death benefits across GPP per capita subgroups and the broader female population with those derived from TMO17, it is evident that TMO17 produces the lowest EPV of death benefits and the highest EPV of survival benefits in these age ranges. On the other hand, this trend reverses for individuals aged 54 to 80. In this age range, the low GPP per capita subgroups demonstrate a higher EPV of death benefits and a lower EPV of survival benefits compared to the female population. However, the high GPP per capita subgroups present an increased EPV of survival benefits and a reduced

EPV of death benefits. A comparison with TMO17 reveals no discernible pattern in the EPV of death or survival benefits across these age ranges.

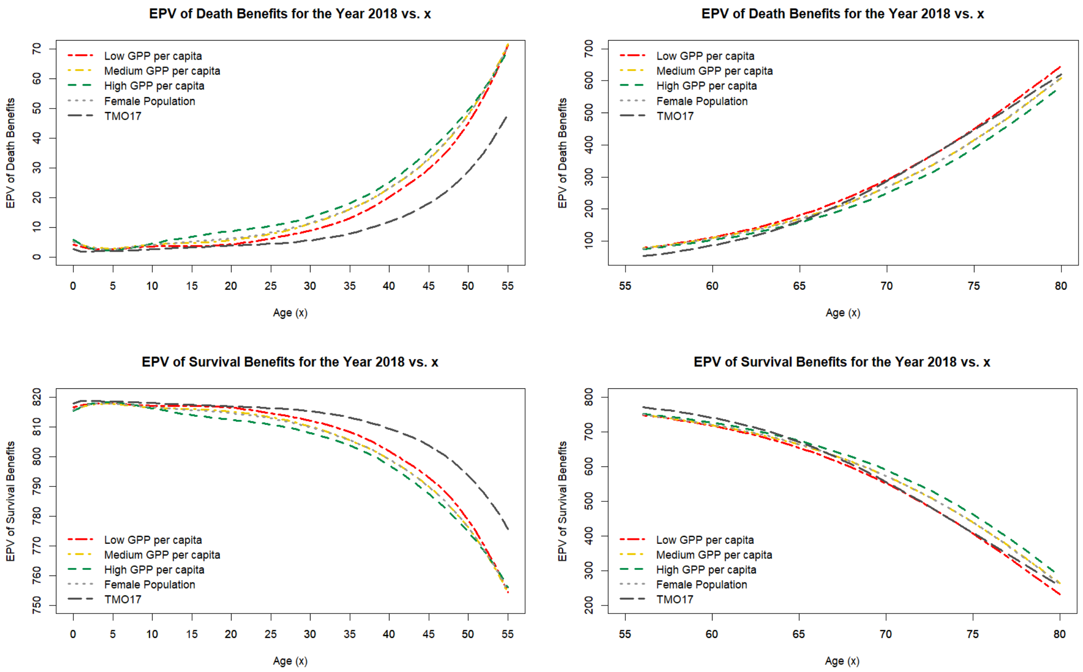

Figure 5 Expected Present Value of Death Benefits and Survival Benefits (in THB per 1,000 THB Sum Assured) for Females at Age x in the Year 2018.

DISCUSSION & CONCLUSION

The research results indicate that the augmented common factor model emerges as the superior choice for both male and female subpopulations due to its robust performance in in-sample fitting and its commendable predictive accuracy in out-of-sample testing. This model effectively captures the complexities associated with socioeconomic mortality differentials, providing a comprehensive framework for understanding mortality trends influenced by socioeconomic status compared to other models.

Moreover, socioeconomic status significantly influences mortality rates across various subpopulations in Thailand. The findings show that individuals within high GPP per capita groups, specifically those aged 70 and older for males and 60 and older for females, have the lowest mortality rates when compared to other subgroups. Higher GPP per capita is typically associated with elevated income levels, which contribute to lower mortality rates. Supporting this assertion, research by Wilkinson (2006) emphasized that higher-income groups benefit from enhanced access to healthcare. Additionally, the impact of GPP per capita should be considered within the context of the relevant area. Regions with high GPP per capita often experienced improved healthcare access, as this economic environment fosters increased investment in healthcare services (Li et al., 2020). The demand for higher-quality offerings incentivizes providers and local governments to enhance their services, resulting in better health outcomes due to the availability of comprehensive and specialized healthcare options. Furthermore, high GPP per capita correlated with health behaviors, which provided individuals with more resources and education to make healthier lifestyle choices (Pampel et al., 2010). In summary, older individuals in high GPP per capita groups derive significant benefits from improved healthcare access, healthier lifestyle choices, and socioeconomic advantages, all of which contribute to lower mortality rates. The correlation between high GPP per capita and reduced mortality rates underscores the role of socioeconomic status and related factors across specific age ranges in high GPP subpopulations.

Notably, this research indicates that specific age ranges—males aged approximately 12 to 65 and females aged approximately 13 to 57—within low GPP per capita subpopulations exhibit the lowest mortality rates compared to other subgroups. Numerous studies demonstrate that high GPP per capita, typically associated with higher income, correlates with lower mortality rates. However, in this context, the findings indicate a divergent pattern. Low GPP per capita subpopulations demonstrate unexpectedly lower mortality rates, while high GPP per capita subgroups display unforeseen higher mortality rates. Several factors may account for this phenomenon. Due to industrial activity, vehicle emissions, and population density, provinces with high GPP per capita, often urban areas, tend to experience elevated levels of air and water pollution, which in turn leads to increased mortality rates. Conversely, provinces with low GPP per capita, usually rural areas, tend to have lower pollution levels, potentially contributing to better health outcomes (Galea & Vlahov, 2005). Additionally, high GPP per capita groups living in urban areas experience heightened levels of chronic stress due to fast-paced lifestyles, overcrowding, noise, and other stressors. Studies confirm that chronic stress is linked to mental health disorders such as depression and anxiety, as well as physical conditions like hypertension and cardiovascular diseases (Cohen et al., 2007). Noise pollution, prevalent in urban settings, was also associated with increased stress levels (Stansfeld & Matheson, 2003). These factors contribute to the higher mortality rates observed in urban, high GPP per capita groups, in contrast to low GPP per capita groups living in rural areas, who typically face fewer stressors. Thus, the divergent health outcomes observed within these age ranges underscore the necessity of considering both environmental determinants and lifestyle choices when analyzing mortality trends across different socioeconomic groups. This anomalous phenomenon can be attributed to the fact that high GPP per capita groups, despite possessing greater resources, may experience declines in health. Such declines may result from lifestyle choices that prioritize work over well-being, as well as increased exposure to pollution and various stressors. Conversely, low GPP per capita groups, who similarly prioritize work, benefit from reduced exposure to environmental pollutants and lower levels of chronic stress. As well, the presence of robust social support networks played an instrumental role in fostering resilience (Holt-Lunstad et al., 2010). These factors collectively contribute to improved health outcomes.

Overall, these findings highlight the critical importance of socioeconomic status and its associations with mortality rates across various subpopulations, as modeled and predicted by the most suitable model, the augmented common factor model. The differential mortality rates associated with varying levels of GPP per capita, which influence both mortality risk and longevity risk, significantly affect the insurance benefits payable to policyholders, as detailed in the life insurance application section. Insurers must carefully consider these complexities to accurately assess risk and develop pricing strategies that reflect the health profiles of distinct subpopulations. This nuanced understanding not only ensures equitable premium rates but also contributes to the long-term sustainability of insurance products tailored to the specific needs.

However, it is important to consider the limitations of this research, as they could potentially facilitate future improvements. The study maintained the same groups based on the percentiles of the weighted average Real GPP per capita for 2023, despite the possibility of changes in subpopulation groups over time. Additionally, Thailand's provincial-level mortality data relies on permanent addresses rather than current addresses, which may introduce discrepancies, particularly in areas with high migration. Moreover, the study emphasizes socioeconomic status solely through income as measured by GPP per capita, whereas socioeconomic status includes other dimensions. Future research should incorporate additional indicators to better capture these dimensions and provide a more comprehensive understanding of socioeconomic mortality differentials. Top of Form

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