LIVING LAB

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Mortality Impact of the COVID-19 Pandemic in East and Southeast Asia

Global Asia
Insurance Partnership

Acknowledgement

The ideation of this research project was jointly developed with the late Professor Ken Seng Tan of Nanyang Technological University. Professor Tan's guidance and suggestions in the early stages of this project, like many of his contributions to the field of actuarial science, were instrumental. This paper has also greatly benefited from the insightful comments and suggestions provided by Richard Lyon, Professor Shinichi Kamiya, GAIP executives, and GAIP partners. The author expresses sincere gratitude for all their contributions.

Global Asia Insurance Partnership

Foreword

Nanyang Technological University (NTU) is a tech-focused institution committed to sustainability initiatives. The Global Asia Insurance Partnership (GAIP) is a tripartite partnership between the insurance sector, the supervisory community and academia with a vision to create a more resilient future for Asia. In support of this vision, GAIP and NTU have entered into a long-term strategic partnership to support GAIP's research and talent development initiatives. Working collaboratively, our aim is to deepen understanding of new, emerging, and accelerating risks that have the potential to shape the insurance sector's future and to collaborate on initiatives to create a more resilient future.

This first comprehensive report, undertaken with the Insurance Risk and Finance Research Centre (IRFRC) at Nanyang Business School as part of GAIP's Living Lab, examines the intricate relationship between the pandemic and mortality trends as identified in different Asian countries and age groups. The report provides analysis and recommendations that can usefully assist both the sector and policy makers as we emerge from the pandemic and enter into a future of living with COVID-19 as endemic, and also flags a range of broader issues associated with the insurance protection gap.

In addition to the detailed findings and practical implications outlined in this report, this report is also a powerful demonstration of the potential of the GAIP-NTU research collaboration through two specific ways. First, GAIP's unique structure creates a bridge between insurance industry and academia which can help narrow the knowledge gap as demonstrated by this report.

Second, this platform enables us to democratise academic knowledge. Policymakers and insurers seeking a comprehensive understanding of the mortality impact during the COVID-19 pandemic will find this report valuable. The insights and recommendations presented herein will foster dialogue, knowledge-sharing, and action, ultimately contributing to the development of resilient insurance ecosystems and narrowing Asia's protection gap.

In closing, we would like to express our appreciation for the efforts of Jessica Dang, the report's primary author, the support of Prof. Shinichi Kamiya (NTU) and Ms. Min Cheng, Senior Director of GAIP, for their invaluable guidance and constructive feedback. We would also like to thank the external reviewers and GAIP partners for their valuable contributions to this report. Their collective efforts have been instrumental in its success.

Sincerely,

Conor Donaldson

CEO, Global Asia Insurance Partnership

Jun-koo Kang

Director, Insurance Risk and Finance Research Centre (IRFRC)

Executive Summary

Since COVID-19 was officially labelled a pandemic on 11 March 2020 by the World Health Organization (WHO), the virus has inflicted significant human, social and economic costs. On 5 May 2023, the WHO declared that COVID-19 no longer "constitutes a public health emergency of international concern"[1]. We are now transitioning from managing a pandemic to living with COVID-19 as endemic.

The mortality impact during the COVID-19 pandemic bears significant ramifications for insurers, policymakers, and a wide spectrum of stakeholders. Numerous studies have been published in recent years examining the impact of COVID-19 on mortality, most of these studies have placed an emphasis on examining the impact of the COVID-19 pandemic on developed countries in Europe and North America. Little has been done to study the mortality impact of the pandemic in East and Southeast Asia, particularly from an actuarial perspective. This study aims at increasing our understanding of the mortality impact of the COVID-19 pandemic in East and Southeast Asia and our forward-looking perspective in regard to mortality on what to expect from COVID-19 as endemic.

This is a technical report conducted as part of the Living Lab of the Global Asia Insurance Partnership. This report details the data analysis performed, explains the stochastic mortality model adopted for the analysis, and based on the analysis, presents our observations and discusses implications and recommendations for life insurers and policymakers.

The focus of the study is the mortality impact from the COVID-19 pandemic. Nonetheless, we also make some observations about the general long-term mortality trend.

The countries we consider in this study are:

- Singapore

[1] https://www.who.int/news/item/05-05-2023-statement-on-the-fifteenth-meeting-of-the-international-health-regulations-(2005)-emergency-committee-regarding-the-coronavirus-disease-(covid-19)-pandemic

- Indonesia
- Japan
- South Korea, which we refer to as Korea hereinafter for brevity.
- Malaysia
- England and Wales (E&W)

We include England and Wales in this study for comparison purpose.

For each of these 6 countries, we conduct the following analysis:

- Analyze their pre-pandemic long-term mortality trend in the past few decades
- Analyze their short-term mortality trend during the COVID-19 pandemic
- Quantify the mortality shock during the pandemic using a stochastic mortality model
- Forecast mortality rates in the next few decades
- Estimate the number of excess deaths during the COVID-19 pandemic and reconcile with excess deaths estimation in other work

Key findings from this study include:

- In aggregate, the mortality experience has deteriorated during the COVID-19 pandemic in the countries we consider.
- Among the 6 countries we considered, Singapore, Japan and Korea have the least impact based on data up to 2022. Thus far they have lost about 4-6 years' worth of mortality improvement because of the pandemic, but the full impact of the pandemic on their mortality remains to be seen. England and Wales lost about a decade's worth of mortality improvement during the pandemic while Malaysia lost about two decades' worth. Indonesia's mortality based on the 2020 data has returned to a level last seen in 1990s.
- The mortality impact also varies by age. In Singapore, Korea, Malaysia and E&W, younger adults experienced a worse shock relative to their normally

low mortality level than older population, although in absolute terms, more older people died during the COVID-19 pandemic than younger people.

- Excess deaths can be estimated using the same stochastic mortality model for modelling the pandemic impact. The estimated excess deaths in these countries are in similar range as excess deaths reported in other studies, which use very different, sometimes much more complicated models.
- Significant tail risk remains in terms mortality risk and longevity risk.
- The long-term trend of mortality improvement in absence of the pandemic in recently developed economies such as Singapore and Korea have slowed down and are converging to the rate of mortality improvement in Japan.

The key implications from the study and our recommendations to life insurance practitioners and policymakers are:

- **Mortality experience monitoring and data collection:** the mortality experience is still evolving and it is important that life insurance players continue to monitor their experience. Timely and granular mortality data collection is crucial to enable better monitoring of mortality experience and prompt quantification of the impacts, in order to inform business practices and public policies.
- **Mortality modelling:** the two-parameter-level model developed in this study can be used as a tool for capturing the age and period-specific impact of mortality shocks, like those caused by the pandemic, enabling insurance companies to assess the impact on their portfolios and make future mortality rate forecasts.
- **Risk management:** life insurance players should seek to diversify their portfolios, avoid concentration in negatively impacted regions and age groups, and look to review the impacts of the pandemic on the Embedded Value of their existing portfolio. We have provided tools to help conduct this assessment under the various scenarios considered. These tools are provided as electronic supplementary materials on the website of Global-Asia Insurance Partnership (GAIP), accessible to GAIP partners. These tools include R codes, simulated mortality rates, and multipliers to mortality rates

based on the simulated mortality rates. In addition, policymakers and regulators should incorporate pandemic scenarios into stress testing and prudential management requirements or update the scenarios where these are already a requirement.

- **Protection gaps:** the study shows that the pandemic has implications on mortality, longevity and health protection gaps, and the pandemic had also highlighted the disparity in the health gap. A holistic, multi-stakeholder approach to addressing the protection gaps, as suggested in the GAIP paper, "About the Protection Gaps", is encouraged.
- **Morbidity impact:** COVID-19 has had an impact on morbidity, leading to increased hospitalizations and delayed care, which has financial and healthcare resource implications. Insurers should study the morbidity impact in their products, and collaboration between governments, insurers, and researchers is encouraged to assess the long-term morbidity impact of the virus.

It is important to note that, like any research project, there are certain limitations within this study. We encourage readers to refer to Section 7 for a more comprehensive discussion of these limitations.

Contents

1 Introduction

We conduct this study to review the mortality experience in the East and Southeast Asia region during the COVID-19 pandemic, evaluate how much the mortality experience has deviated from its long-term trend, and assess the trajectory and range of outcomes of how mortality may evolve in the next few decades. In absence of an industry-wide study of the mortality experience during the COVID-19 pandemic, this report attempts to offer a timely update of the impact on overall population mortality in this region. We hope the results and discussions presented in this report will inspire life insurance practitioners in the region to conduct a forward-looking evaluation of the COVID mortality impact in their own portfolio. To that end, this report serves as a technical roadmap on how such exercise may be carried out. The numerical results presented in the report can also be used as a baseline for comparison.

We choose to study Singapore, Indonesia, Japan, Korea and Malaysia because these are the countries for which we can find reliable mortality data during the COVID-19 era. We estimate the magnitude of mortality shocks in these countries since 2020 so that we can compare the mortality impact by country, by time periods, and by age groups, and make forecasts on how the shocks may dissipate. Given the uncertainty on how the elevated mortality level during the pandemic may return to normal, we utilize Monte Carlo simulations to gain insight into the distribution of outcomes we may expect in the future. In particular, the Monte Carlo simulations reveal the size of the tail risk in mortality and in longevity.

2 Mortality Data and Pre-pandemic Mortality Trend

To study mortality trends in the East and Southeast Asia region, we start by gathering mortality data for countries and territories in this part of the world. We collect population mortality data from publicly available sources such as the Human Mortality Database[2], United Nation's World Population Prospects 2022[3], and national statistical offices in some countries. Details of the data source for each country and modifications made to data from these sources are outlined in Appendix A. The modifications are made to close small gaps in the data so that the data conform to the format we require for our modelling purposes.

In this section, we present the age-standardized mortality rates of the countries we collected data from, discuss their life expectancies and apply a stochastic mortality model to quantify their long-term mortality trend.

2.1 Age-standardized mortality rate

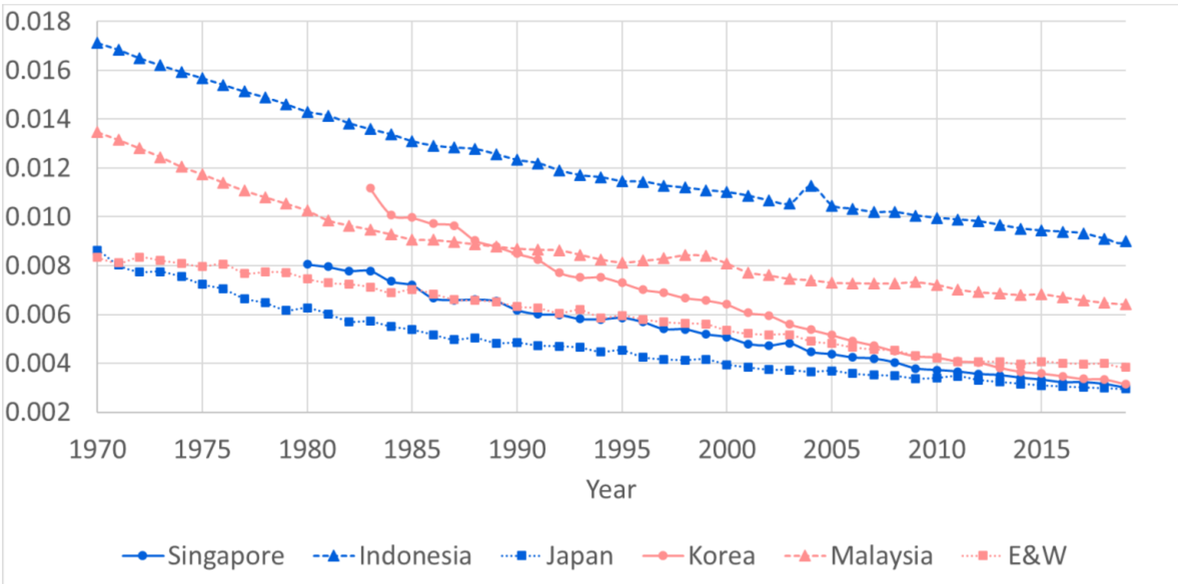
Figure 1 depicts the evolution of age-standardized mortality rates in each of the six countries over the period we collect mortality data for, up to 2019. The age-standardized mortality rates are calculated based on the age mix in the WHO standard population (Ahmad et al., 2001). Interested readers may find such age mix in Figure 28 in Appendix A.

The standardized rates allow us to fairly compare the overall mortality rate across different countries, but by definition the age-standardized mortality rates differ from the overall mortality rates of each country. It is worth noting that in this illustration, the age-standardized mortality rates do not reflect the change in the population age-mix over the observation period in each individual country, which can be substantial for some.

[2] https://www.mortality.org/
[3] https://population.un.org/wpp/

Figure 1 suggests that since 1970, the mortality rates have improved in all six countries considered. However, there are still clear gaps in the absolute level of mortality among these countries. Indonesia has the highest level of mortality while Malaysia ranks the second highest. Note that the hump observed in the Indonesia mortality rates is caused by the 2004 Indian Ocean tsunami. Singapore and Korea also had elevated mortality rates in the past, but the experiences have quickly improved and have now reached similar levels to Japan and England and Wales. The speed of improvement varies by country and by time periods. We will explore the trend in mortality improvement more closely in Section 5.1.

Figure 1: Age-standardized mortality rate of Singapore, Indonesia, Japan, Korea, Malaysia and England & Wales from 1970 to 2019, where data are available. The age-standardized mortality rate is a weighted average of age-specific mortality rates, where the weights are based on the age mix of the WHO standard population (Ahmad et al., 2001).



2.2 Life expectancy

In this section, we review the two definitions of life expectancy, a commonly used measure of overall mortality level in a population and explain their similarities and differences.

Let $\mu_{x,t}$ denote the force of mortality at age x in time t. The period life expectancy at age x in time t, which we denote as $e^P_{x,t}$, is calculated as

$e_{x,t}^{P} = \sum_{u=0}^{\infty} e^{-\int_0^u \mu_{x+s,t} ds}$.

It can be interpreted as the mean age of death for a hypothetical cohort of age x at time t, whose mortality experience follows the age-specific mortality rates as of time t. In other words, the period life expectancy ignores any mortality improvement that is expected to occur to this cohort from time t and beyond. Therefore, the cohort in the definition of period life expectancy is only considered a hypothetical one. Despite the drawback of ignoring long-term mortality improvement, period life expectancy provides a snapshot of the overall mortality level of a population in any given year. It is also the life expectancy measure commonly cited in official statistics or newspaper articles.

In contrast, the cohort life expectancy at age x in time t, which we denote as $e_{x,t}^{C}$, is calculated as

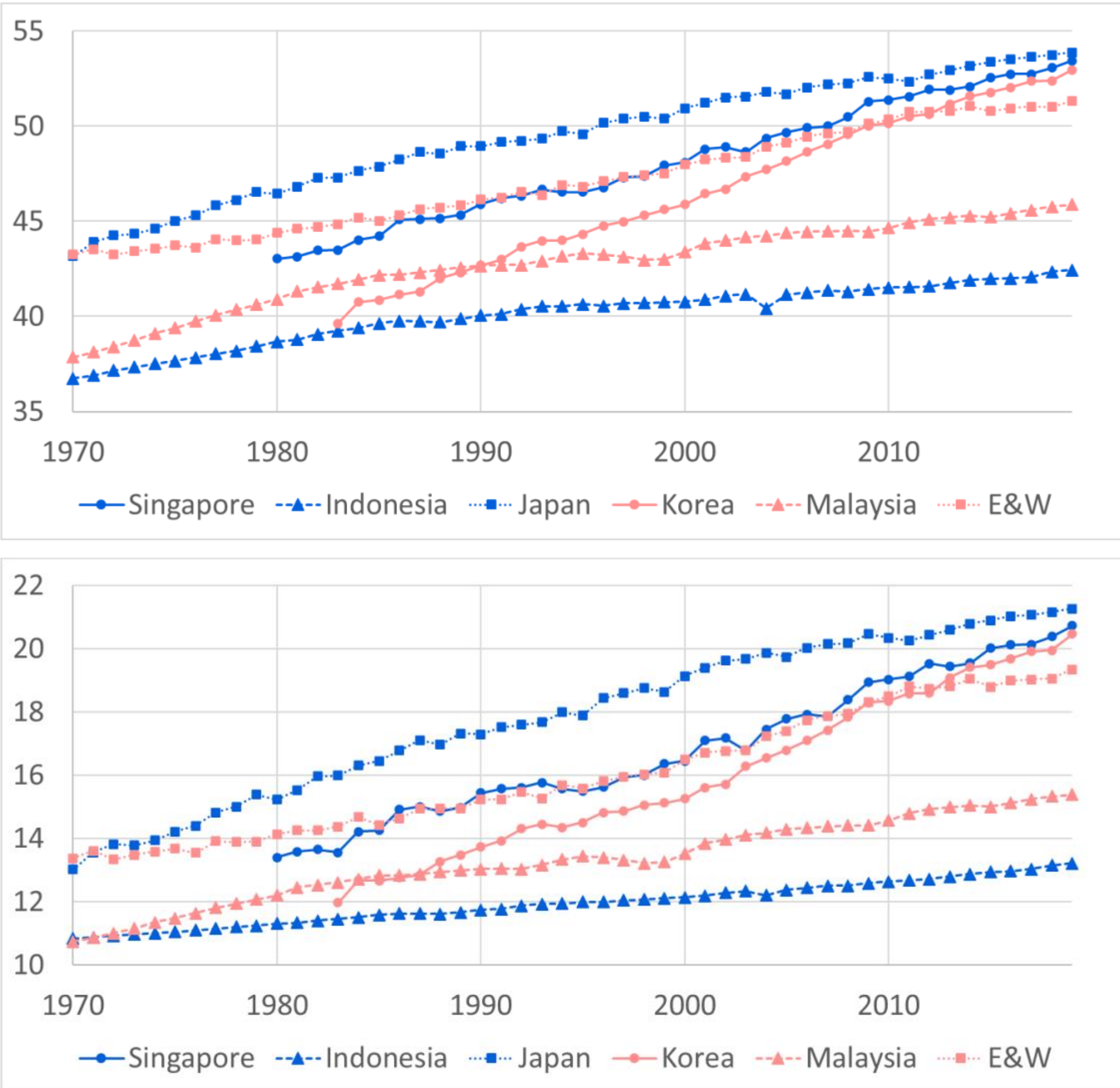
$e_{x,t}^{C} = \sum_{u=0}^{\infty} e^{-\int_0^u \mu_{x+s,t+s} ds}$.

It can be interpreted as the mean age of death for a cohort of population with age x at time t, whose mortality experience follows the natural evolution of mortality rates since time t. This is a more realistic measure of how long a cohort at a certain age is expected to live. For example, if an insurance company were to insure an age x in year t, then the insurer should expect the age x to live for $e_{x,t}^{C}$ years, rather than $e_{x,t}^{P}$ years, on average. However, measuring the cohort life expectancy from historical data would require a long history of data that cover a cohort's mortality experience from birth to extinction. Reliable cohort data are often unavailable, especially in developing countries. In addition, projection of future cohort life expectancy is sensitive to the assumptions chosen for future mortality improvement.

We should caution that under the assumption of steady future mortality improvement, the period life expectancy will understate the longevity of a cohort compared to the cohort life expectancy, sometimes quite substantially. Interested readers can refer to Guillot (2011) for a comprehensive discussion of period versus cohort life expectancy.

Figure 2 illustrates the period life expectancy as of age 30 and age 65, respectively, from 1970 to 2019 where data are available.

Figure 2: Historic Period life expectancy from 1970-2019 of age 30 (upper panel) and age 65 (lower panel) of Singapore, Indonesia, Japan, Korea, Malaysia and England & Wales.



The trend in period life expectancy at both age 30 and age 65 mirrors the trend in age-standardized mortality rates we observe in Figure 1 to a large extent. The most noticeable difference between Figure 1 and Figure 2 is that the gap in life expectancy between Indonesia and the other countries seems much smaller than the gap in their age-specific mortality rates. This is due to the much higher infant mortality in Indonesia than the other countries, particularly in the earlier data periods. Given infant mortality has no impact on period life expectancy at age 30 or 65, the gaps between Indonesia and the other countries in Figure 2 seem much smaller than in Figure 1. It is also worth noting that in 2019 the life expectancy at age 65 (20.7 years) in Singapore is 57% longer than that in Indonesia (13.2 years), and 35% longer than that in Malaysia (15.4 years). This signifies remarkable differences in the need for retirement income among these countries in current times, and room for future mortality improvement in less developed countries such as Malaysia and Indonesia.

2.3 Stochastic mortality model

Movement in mortality over time can be attributed to trend, shock and an idiosyncratic component (Dickson et al., 2019). The trend describes the gradual change in mortality over a long period of time, although the degree of the gradual change varies by age. Shock refers to any short-term sharp change to mortality, like a war or the COVID-19 pandemic. The idiosyncratic component captures the remaining random variation in the mortality changes. For example, in Figure 1, the generally decreasing slope of the mortality rates in each country shows the trend of mortality movement; the occasional bump in the mortality data series, for example the hump in 2004 in Indonesia due to the Indian Ocean tsunami or the increase in mortality rates after 2019 due to COVID which we will see in Section 3.3, are shocks; the fluctuations year-on-year along the generally decreasing line of historical mortality rates are the idiosyncratic component.

A well-designed stochastic model can reflect all three components of mortality variations and allows us to forecast future mortality with all three components taken into consideration. For this reason, we use stochastic mortality model for this study.

2.3.1 The Lee-Carter Model

The Lee-Carter model (Lee & Carter, 1992) is a classic model for long-term mortality trend. Let $m_{x,t}$ denotes central death rate at age x in year t. The model assumes the log central death rate is described by a stochastic process as follows:

Equation 1: The Lee-Carter Model

$$\log m_{x,t} = a_x + b_x k_t + \xi_{x,t}$$

where k_t follows a random walk with drift such that

$$k_t = k_{t-1} + \mu + \epsilon_t, \qquad \epsilon_t \overset{i.i.d.}{\sim} N(0, \sigma^2)$$

In this model, a_x represents the long-term average log central death rate of age x over the data period; k_t captures the overall change in mortality level over time and is also known as the mortality index; b_x reflects age x's sensitivity to changes in k_t; $\xi_{x,t}$ is a random error that is typically small and we assume it is negligible in this study.

As its structure suggests, the Lee-Carter model captures the trend and idiosyncratic component of the mortality changes over time, but it fails to consider any shocks. Thus, in Section 4.1 we describe how we use a two-parameter-level model to estimate the impact from the COVID-19 pandemic.

2.3.2 Estimated parameters of Lee-Carter model

We estimate parameters in the Lee-Carter model using data up to 2019. Table 1 shows the estimated μ and σ, which describe the random walk with drift process that k_t follows.

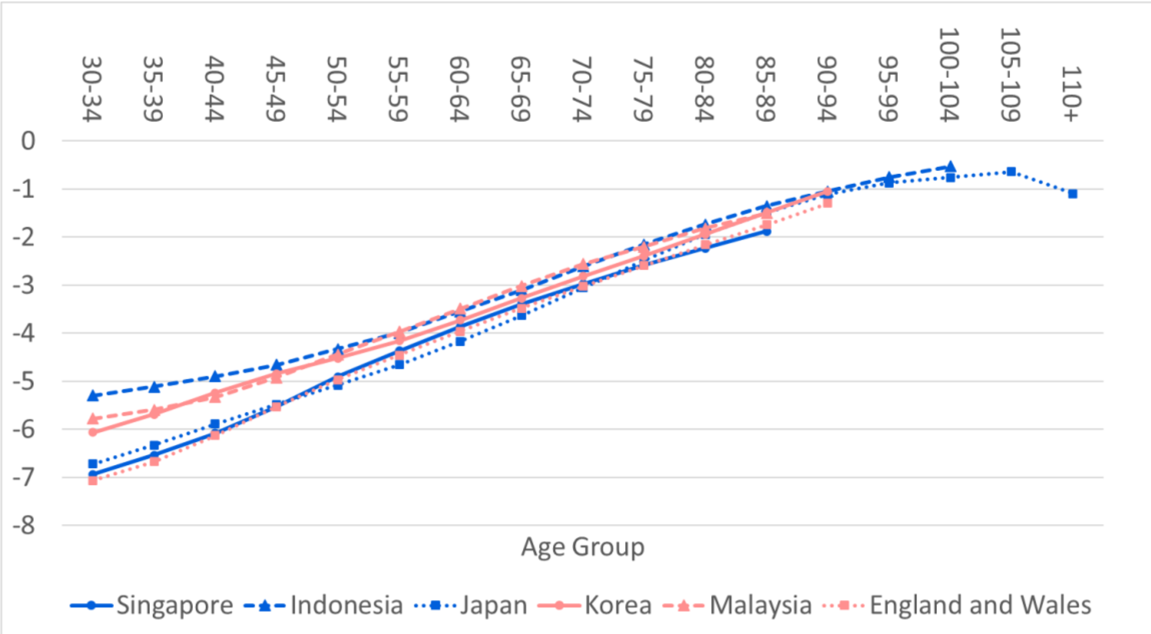
Table 1: Estimated μ and σ from the Lee-Carter model based on pre-pandemic data

	Singapore	Indonesia	Japan	Korea	Malaysia	E&W
μ	-0.331	-0.148	-0.270	-0.494	-0.179	-0.187
σ	0.196	0.238	0.260	0.230	0.153	0.232

Figure 3 to Figure 5 show parameters a_x, b_x and k_t estimated from the Lee-Carter model. A few observations can be drawn from the parameters estimated:

- There is larger variation in the estimated values of a_x, the long-term average log central death rate of age x over the data period, between different countries at younger ages than older ages. The variation in a_x at younger ages reflects the variation in socioeconomic development as well as accessibility and quality of health care in these countries. On the other hand, the smaller variation in a_x at older ages reflects the natural force of aging.

Figure 3: a_x estimated with pre-COVID data fitted to the Lee-Carter model.



- The estimated values of parameter b_x, which represents the sensitivity of the mortality rate in each age group relative to long-term mortality trend, show that the range and shape of such sensitivity across different age groups differ by country. More specifically, the range of b_x is larger in developing countries like Indonesia and Malaysia than the comparison countries, suggesting greater variation in how much the mortality rates are improving across age groups relative to the overall long-term mortality trend. In addition, the sensitivity tends to peak at the youngest age group in Indonesia, Korea and Malaysia but only peak at age 65-75 in Singapore, Japan and E&W. This suggests that in Indonesia, Korea and Malaysia, the younger age groups' mortality is improving the most relative to the other age groups but in Singapore, Japan and E&W, it is the 65-75 age groups that are improving the most, relatively speaking.

Figure 4: b_x estimated with pre-COVID data *fitted to the Lee-Carter model.*

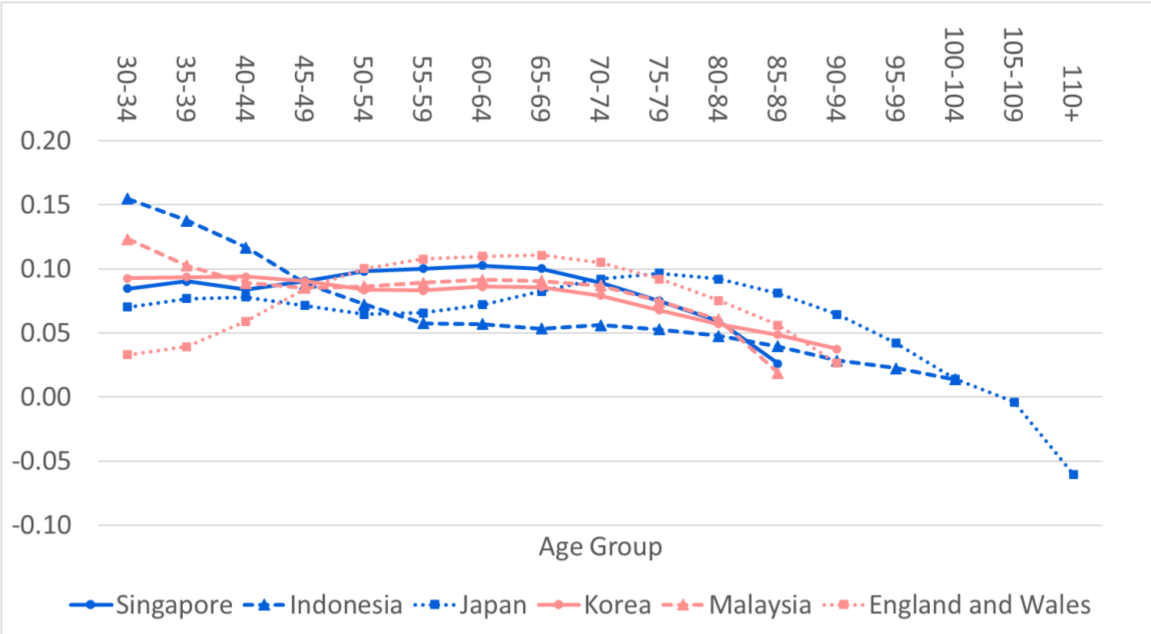
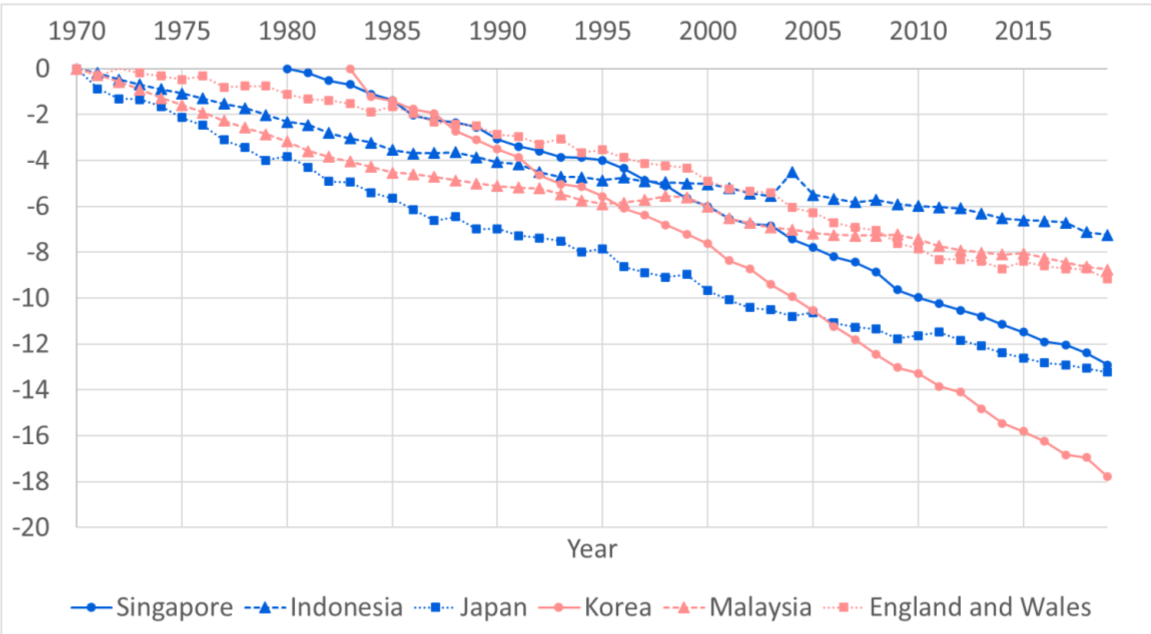


Figure 5: k_t estimated with pre-COVID data *fitted to the Lee-Carter model.*



- The overall long-term mortality trend measured by parameter k_t varies from country to country and the trend is commensurate with the long-term trend we observe in Figure 1. The hump in 2004 in Indonesia is an indication that k_t in Indonesia may not follow the random walk with drift in the Lee-Carter model, but we ignore this deficiency given the focus of this study is the mortality impact from COVID-19.

3 Mortality Trend in the COVID-19 Pandemic

In this section, we discuss factors that contribute to the mortality shocks during the COVID-19 pandemic and examine the empirical evidence of these shocks.

3.1 Factors impacting mortality during the COVID-19 pandemic

The COVID-19 pandemic has led to shocks to mortality experience that deviate from the long-term trend. The shocks to mortality can be broadly attributed to a number of sources. We list these sources in descending order of significance, first for those contributing to excess deaths and then for those contributing to avoided deaths in the pandemic.

- **Excess deaths** due to acute COVID-19 infection.
    - The SARS-CoV-2 virus often causes suppurative pulmonary infection which leads to septic shock and multi organ failure, and eventually results in deaths (Elezkurtaj et al., 2021).
    - The virus could also impact cardiovascular system and cause deaths (Long et al., 2020).
    - Risk factors for mortality caused by COVID-19 infection include older ages, male sex, obesity, and comorbidity such as hypertension, diabetes, cardiovascular disease and cancer (Elezkurtaj et al., 2021; Noor & Islam, 2020; Zhang et al., 2023).
    - Disadvantaged socioeconomic status has also been identified as a risk factor in many studies (Hawkins et al., 2020; Wachtler et al., 2020; Yates et al., 2022).
    - Post-acute sequelae of COVID-19 can lead to worse health outcomes and even deaths. Al-Aly et al. (2021) show that 30 days after COVID-19 infection, people exhibit a higher use of health resources and risk of death. The study identifies that the SARS-CoV-2 virus can cause damage in multiple organs and systems in human body.

- **Excess deaths** due to delayed medical care, avoidance of medical care, and strain on the health care system.
    - Czeisler et al. (2020) showed that since the start of the pandemic to June 2020, as much as 41% of adults in U.S. had delayed or avoided medical care. Among them, some of the more physically vulnerable groups such as people with underlying medical conditions and with disabilities are more prevalent in avoiding urgent care.
    - In Wai et al. (2022), it is identified that there was a significant reduction in emergency department visits in the first 8 months of the COVID-19 pandemic in Hong Kong, which was associated with an increase in deaths certified in the emergency department. The findings suggest that people are avoiding emergency care during the pandemic, and the avoidance of care resulted in patients ending up in the emergency department in a worse state than the pre-pandemic trend and dying at a higher rate.
    - Dang et al. (2022) studies Medicare hospital admissions in over 4,000 U.S. hospitals. They found that admission for non-COVID diagnoses have fallen sharply since March 2020 and remained low through September 2021. However, the mortality after hospitalization for non-COVID diagnoses has risen by more than 20% and the increase in mortality is even higher in hospitals with high COVID-19 caseloads. The authors identify disruption to healthcare access due to COVID-19 as a cause for the increase in mortality.

- **Excess deaths** due to change in behaviour during the pandemic.
    - White et al. (2022) showed that in the U.S., alcohol-related deaths increased by about 25% in 2020 compared to 2019, while the number of opioid overdose deaths increased by 38% and the number of deaths involving synthetic opioids such as fentanyl increased by 55%.

- **Avoided deaths** due to reduction in other transmissible diseases such as influenza and pneumonia as a result of the non-pharmaceutical intervention (NPI) measures in place to reduce COVID-19 infection.

  - Hills et al. (2020) points out that influenza infections during the 2020 influenza season in Australia and New Zealand was at historically low levels, and the authors attribute it to NPIs in place.
  - According to Kung et al. (2021), in New Zealand, between week 13 – 42 of 2020, the mean weekly all-cause death rate was 11% lower than in 2015–19.

- **Avoided deaths** due to fewer road traffic and occupational accidents, as well as reduced air pollution due to lock-down. This could be an important contributing factor in the densely populated East and Southeast Asian countries.
  - Chen et al. (2020) shows that the lock-down measures implemented in Wuhan, China in early 2020 to contain the COVID-19 outbreak led to improvements in air quality, which reduced non-COVID-19 deaths by around 9,000. About 65% of the reduction in deaths is attributed to cardiovascular disease and Chronic Obstructive Pulmonary Disease.
  - Yasin et al. (2021) shows decrease in annual road death in 33 out of 42 countries in 2020 compared with 2019, some as much as 25%.

3.2 Reported COVID deaths and all-cause deaths

The level at which excess deaths occurred vary significantly between countries, among different age groups within a country, and across different time periods during the COVID-19 pandemic. Hence, we study in more detail different statistics of the mortality data in these countries before and after the COVID-19 pandemic.

In this study, we focus on all-cause mortality during the COVID-19 pandemic rather than COVID-related mortality because the all-cause mortality reflects the true burden each country has taken on during the pandemic. This also avoids any inconsistency in the definition of COVID-related deaths. The definition of “die with” versus “die of” COVID-19 varies by countries and even within a country, the definition varied at different times during the pandemic. The gap in the capability to accurately track and report COVID-related deaths also jeopardizes a fair comparison of mortality experience between countries.

Nevertheless, to provide more context for our analysis, we compare in Table 2 the COVID-19 deaths per 1,000 population and change in all-cause deaths per 1,000 population in the data we gathered. The COVID-19 deaths for all countries but E&W are reported by the World Health Organization whereas the COVID-19 deaths for E&W are reported by the Office for National Statistics, UK. The blank entries represent data not yet available.

Table 2 shows that the reported COVID deaths cannot fully explain the change in all-cause mortality since the pandemic in any case. This is as expected because multiple factors contribute to shocks to all-cause mortality during the pandemic, as discussed at the beginning of Section 3.1. Interestingly, for E&W the reported COVID deaths in 2020 and 2021 exceed the increase in all-cause deaths from 2019. This could be caused by several factors contributing to all-cause deaths that offset each other.

Table 2: Deaths per 1,000 population - COVID vs. all-cause deaths

	COVID deaths			All-cause deaths	Change in all-cause deaths from 2019		
Country	2020	2021	2022	2019	2020	2021	2022
Singapore	0.01	0.20	0.22	5.04	0.14	0.78	1.24
Indonesia	0.08	0.45	0.06	7.54	1.43		
Japan	0.03	0.12	0.31	11.15	-0.03	0.56	1.10
Korea	0.02	0.09	0.52	5.75	0.19	0.43	1.45
Malaysia	0.01	0.94	0.16	5.25	-0.19	1.53	
E&W	1.46	1.24	0.55	8.95	1.29	0.88	0.77

3.3 Age-standardized mortality rate and life expectancy

Figure 6 and Figure 7 illustrates the age-standardized mortality rate and period life expectancy, respectively, of each country from 2015 to 2022, where data are available.

Figure 6: Age-standardized mortality rate of Singapore, Indonesia, Japan, Korea, Malaysia and England & Wales from 2015 to 2022, where data are available. The age-standardized mortality rate is a weighted average of the age-specific mortality rates, where the weights are based on the age mix of the WHO standard population (Ahmad et al., 2001).

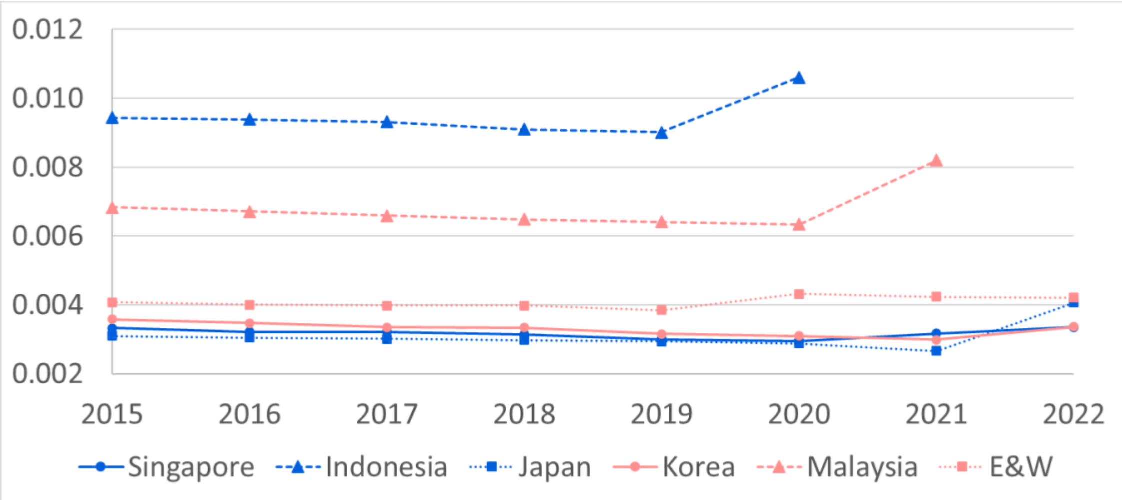
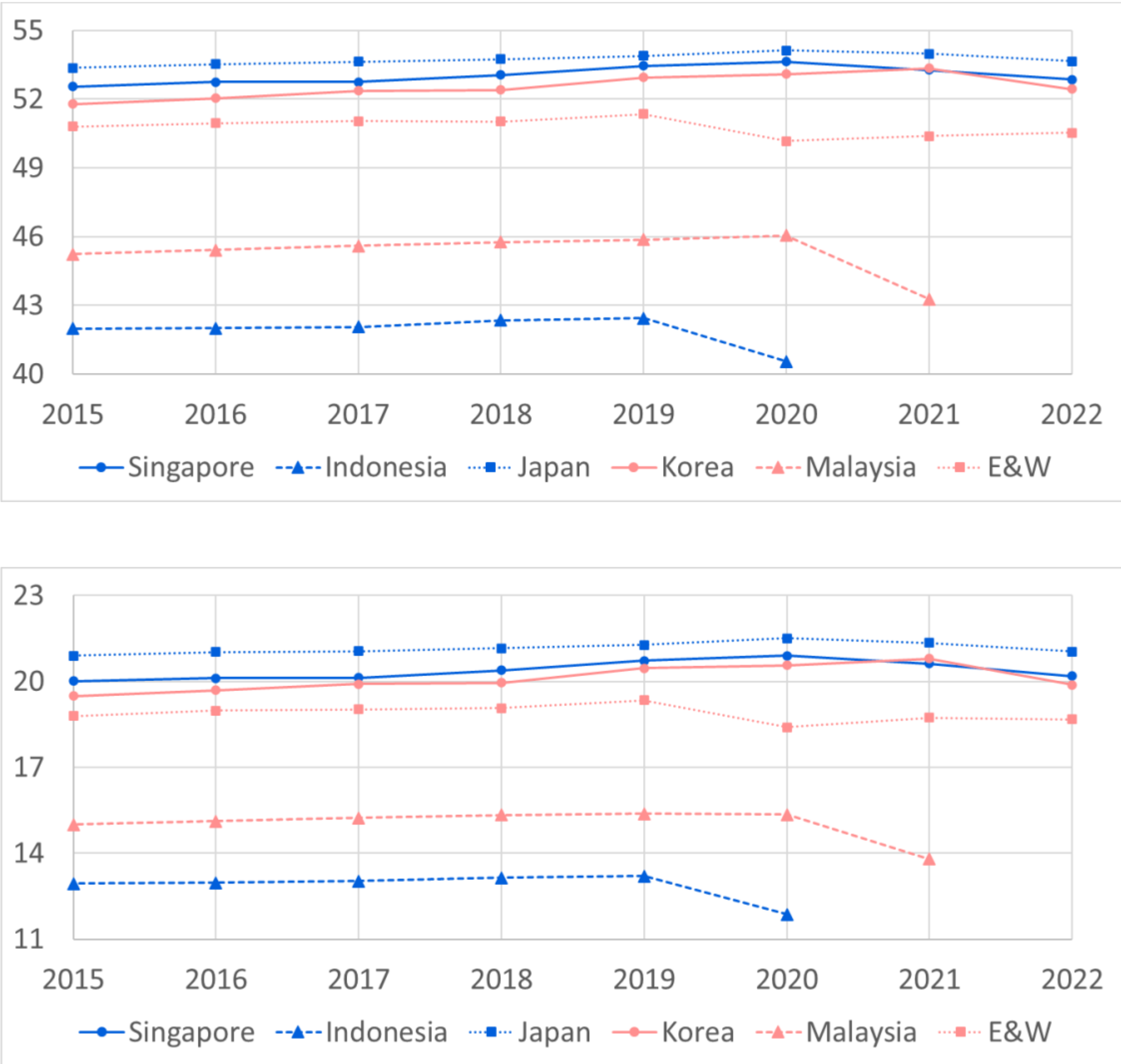


Figure 6 shows that the mortality rates in all the Asian countries we study deviate from the trajectory of their historical trend due to the COVID-19 pandemic, but the timing and the magnitude of such deviation varies by country.

Most notably, the less developed countries such as Indonesia and Malaysia have observed much higher mortality increase than the more developed countries such as Japan, Korea, and Singapore. In Indonesia, the significant increase in mortality can be observed as early as 2020 whereas the other four Asian countries all observed a small mortality improvement in 2020, primarily as a continuation of the pre-pandemic trend. The mortality rates in Singapore and Malaysia increased in 2021, mostly driven by the Delta variant and the onset of the Omicron variant of the SARS-CoV-2 virus, whereas the mortality rates in Japan and Korea continues to decrease slightly in 2021. In 2022, Singapore and Korea had steady increase in mortality while Japan observed a larger increase in mortality rates in 2022. It is worth highlighting that the mortality experience of England and Wales was already worse than Japan, Korea, and Singapore, before the pandemic. Its mortality rates deteriorated even further since 2020 and remained elevated through 2022.

The period life expectancy shown in Figure 7 depicts a similar impact from the pandemic as we observe in the age-standardized mortality rates in Figure 6.

Figure 7: Period life expectancy of age 30 (upper panel) and age 65 (lower panel) of Singapore, Indonesia, Japan, Korea, Malaysia and England & Wales.



In Figure 8 and Figure 9, we compare the period life expectancy in 2022 projected based on pre-COVID mortality trend from the Lee-Carter model with their actuals. The comparison helps evaluate the impact caused by the COVID-19 pandemic on period life expectancy in 2022. We also show the last time that the period life expectancy was below the 2022 actual. For example, in Korea, $e^P_{30,2022}$ is 52.4, and the last time $e^P_{30,t}$ was as low as 52.4 in Korea was in 2018. The results also suggest that Malaysia and Indonesia each lost about 20 years' worth of mortality improvement during the pandemic, although the impact for Malaysia is less severe in older ages. England and Wales also lost about 10 years' worth of mortality improvement.

Figure 8: Period life expectancy $e^P_{30,2022}$ pre and post pandemic trend

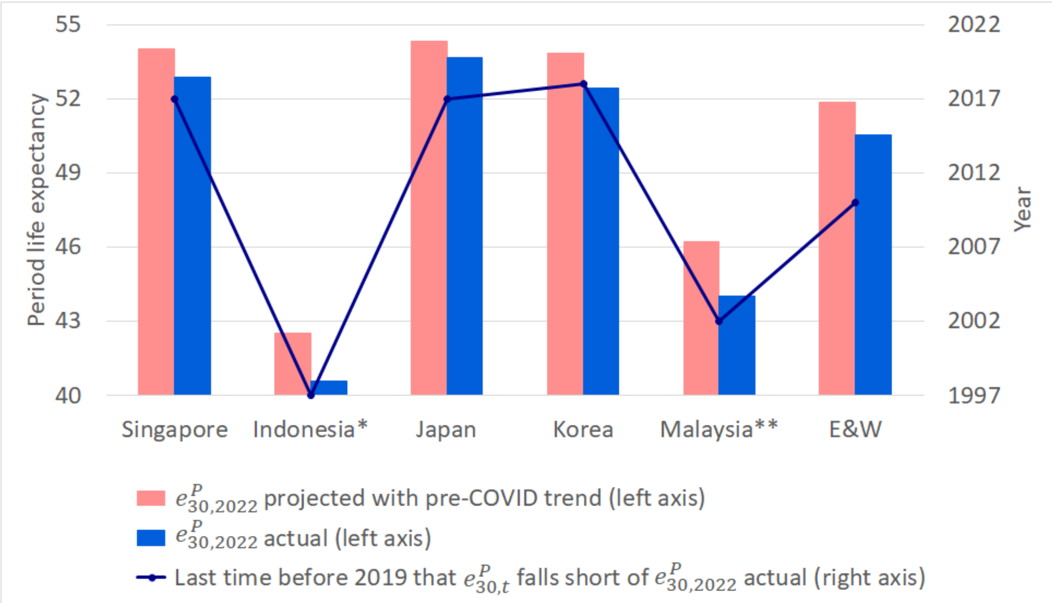
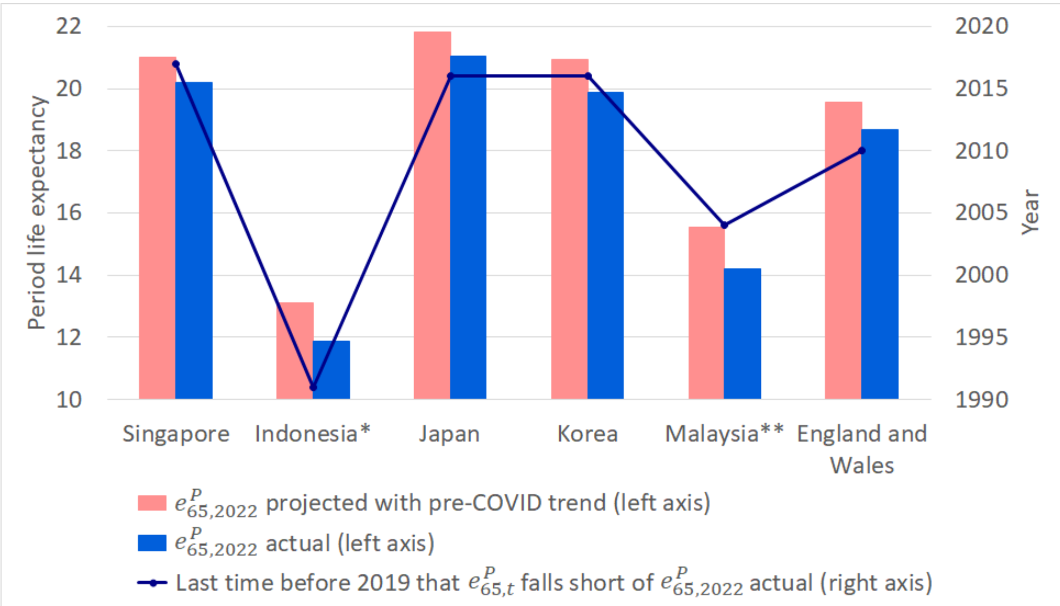


Figure 9: Period life expectancy $e^P_{65,2022}$ pre and post pandemic trend



* For Indonesia, the comparison is between expected and actual $e^P_{30,2020}$.
** For Malaysia, the expected $e^P_{30,2022}$ is based on mean of simulated death rates. Detail of the simulation is discussed in Section 5.

3.4 Age-specific Excess Mortality due to COVID-19 Pandemic

Figure 10 is a heatmap of percentage of change in age specific mortality rates in each country during the COVID-19 pandemic from the expected mortality rates projected based on their long-term mortality trend. In other words, the graph shows the excess (positive) or avoided (negative) death rates as a percentage of the long-term mortality rates. The percentage of changes are estimated using the two-parameter-level model which we will discuss in detail in Section 4.

Figure 10: Estimated excess mortality rate as a percentage of expected mortality rates based on long-term trend. Excess mortality is estimated as $(e^{c_{x,t}\pi_t \mathbf{1}_{t\in\mathcal{T}}} - 1)$ *using the two-parameter-level model in Section 4.*

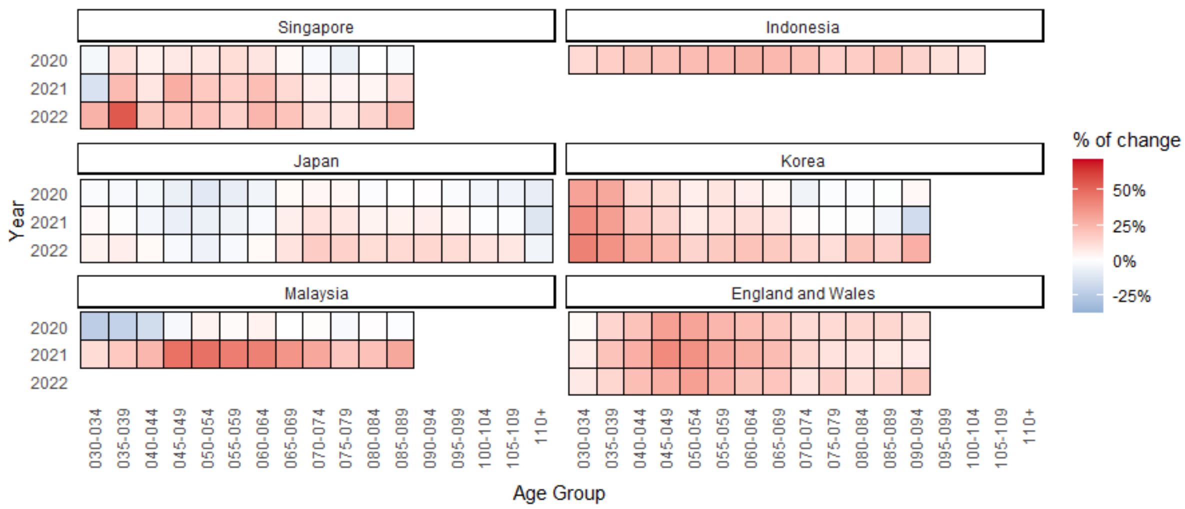


Figure 10 shows that each country in our study presents a unique trend in age-specific mortality rates compared to their expected mortality rates:

- **Singapore**: Excess mortality gets worse year over year from 2020 to 2022. Apart from age 30-34 and 85+, younger age groups experience worse excess deaths as a percentage of their normally low mortality level than older age groups.
- **Indonesia**: Significant excess deaths are observed in all age groups in 2020.
- **Japan**: For ages 45-65, the data suggest avoided deaths from 2020-2022. For ages above 65, excess mortality gets worse year over year from 2020 to 2022.

The heatmap suggests avoided deaths in ages 110+, but data are scarce in that age group so the result may not be reliable.

- **Korea**: Excess mortality gets worse year over year from 2020 to 2022. Similar to Singapore, younger age groups experience worse excess deaths as a percentage of their normally low mortality level than older age groups. In ages 70+, we see avoided deaths in 2020-2021.
- **Malaysia**: In 2020, ages below 45 observe noticeable avoided deaths, whereas for ages above 45, the impact is very muted. In 2021, there are large amount of excess deaths in all ages, with ages 45-74 being the worst.
- **England and Wales**: There are excess deaths in all age groups from 2020 to 2022, with 2021 being the worst year. Younger age groups tend to suffer worse excess deaths as a percentage of their normally low mortality level than older age groups.

4 Estimating the Impact on Mortality during the COVID-19 Pandemic

In this section, we describe the stochastic mortality model we adopt to estimate the long-term mortality trend and the impact on mortality from the COVID-19 pandemic for each country of interest. We also present results from the model parameter estimation and discuss their implications. In addition, we illustrate how we use the model to estimate excess deaths.

4.1 A Two-parameter-level Model

We use a two-parameter-level adaptation of the multi-parameter-level model in Zhou & Li (2022) to fit our mortality data. More specifically, the two-parameter-level model assumes that $D_{x,t}$, the number of deaths at age x in year t, follows a Poisson distribution with a mean of $E_{x,t}m_{x,t}$, where $E_{x,t}$ denotes the number of exposures-at-risk at age x in year t.

Let $\mathcal{T} := \{T_1, \dots, T_k\}$ denote the set that includes all k years in which a pandemic takes place. In this study, we deem the COVID-19 pandemic to be ongoing from 2020 to 2022 so $\mathcal{T} := \{T_1 = 2020, T_2 = 2021, T_3 = 2022\}$. The model further assumes that the log central death rate is described as a stochastic process in Equation 2.

Equation 2: The two-parameter-level model

$$\log m_{x,t} = a_x + b_x k_t + c_{x,t} \pi_t \mathbf{1}_{t \in \mathcal{T}}$$

where k_t follows the same random walk with drift as in Equation 1 and $\mathbf{1}_{t \in \mathcal{T}}$ is an indicator function with value of 1 if $t \in \mathcal{T}$ and 0 otherwise.

Given a set of mortality data covering ages $x_1, \dots, x_m$ from year $t_1, \dots, t_n$, to ensure uniqueness of the parameters, we impose the following constraints.

$$\sum_{x=x_1}^{x_m} b_x = 1, \qquad k_{t_1} = 0, \qquad \sum_{x=x_1}^{x_m} c_{x,t} = 1.$$

In this two-parameter-level model, the first parameter level is the classic Lee-Carter model, represented by $a_x + b_x k_t$, for modelling long-term mortality trend. The second parameter level in the model, represented by $c_{x,t}\pi_t\mathbf{1}_{t\in\mathcal{T}}$, captures the short-term shock to mortality due to the COVID-19 pandemic. Given this set-up, the model assumes that the long-term mortality is multiplied by a factor of $e^{c_{x,t}\pi_t\mathbf{1}_{t\in\mathcal{T}}}$ due to the short-term impact of the COVID-19 pandemic, and excess mortality as a percentage of long-term expected mortality is $\left(e^{c_{x,t}\pi_t\mathbf{1}_{t\in\mathcal{T}}} - 1\right)$. This is how we quantify the excess mortality shown in Figure 10 in Section 3.4. The parameter π_t resembles k_t, and measures the overall impact of the shock in each year of the pandemic. The parameter $c_{x,t}$ resembles b_x, and measures different levels of sensitivity of each age x to the overall shock at time t. Note that unlike b_x which only differs by age, $c_{x,t}$ varies both by age and time. This is a useful modelling feature as we observed in Figure 10 that the degree at which mortality rate changes during the COVID-19 pandemic indeed varies by age and time.

In addition to the flexibility offered by the age-varying and time-varying shock component, this model offers several other benefits:

- The two-parameter-level structure allows easy segregation of impact from long-term trend and that from short-term shock.
- The segregation of trend and shock then enables us to easily layer on impact from pandemic events in forecasting future mortality.
- The relatively parsimonious structure of the model makes estimation of parameters fast and reliable.

Nonetheless the main limitation of this model is that the shock component is deterministic in the sense that it assumes no random variation in terms of the period effect or the age effect of the shock so it is not a model that can be applied to model *any* generic mortality shocks. The timing of the shock component is also superimposed by the indicator function $\mathbf{1}_{t\in\mathcal{T}}$, so the model is not capable of automatically detecting mortality shocks. In addition, the model does not capture any cohort effect, which is the mortality trend specific to a cohort in the population, in the long-term trend. The cohort effect in the populations that we consider may be material, but to quantify it together with the mortality shock during the pandemic using a stochastic mortality model requires more sophisticated methods and is beyond the scope of this study. More importantly, in this study we focus on the mortality impact from COVID-19 by quantifying the mortality shock as multipliers relative to the mortality rates according to long-term trend, and by comparing statistics such as life expectancies before and after the pandemic and between different future scenarios. In these exercises, the cohort effect of any existing cohorts will not affect the net pandemic impact that we analyze. Moreover, to identify and quantify any cohort effect that might have been caused by the COVID-19 pandemic, it would require more years of mortality data beyond 2022.

4.2 Estimated parameters of the two-parameter-level model

We fit the two-parameter-level model to the mortality data of each country we are interested in. The data periods we use for model estimation are listed in Table 3 below.

We only modelled mortality rates for age 30 and above because mortality rates for those under 30 could be very volatile due to small sample sizes, especially in countries with small population like Singapore, and could easily distort estimation of the model. In addition, truncating the data below age 30 does not materially affect the utility of this work for life insurers.

We follow the work of Zhou & Li (2022) for parameter estimation. We treat the model as a Generalized Linear Mixture Model (GLMM) and estimate the parameters by maximizing its penalized quasi-likelihood (PQL) of the model. We chose this estimation method over the two-stage maximum likelihood estimation method commonly used in estimating parameters in Lee-Carter model as the PQL estimation method ensures the impact from mortality shocks is fully captured by the second parameter level $c_{x,t}\pi_t\mathbf{1}_{t\in\mathcal{T}}$ and does not distort the estimated values of parameters a_x, b_x, and k_t in the first parameter level, which the two-stage maximum likelihood estimation method fails to achieve. We discuss in detail the PQL estimation method in Appendix B.1.

Table 3 summarizes the pre-pandemic and pandemic data periods we use in each country, as well as the μ and σ estimated from the two-parameter-level model, which describes the random walk with drift process that k_t follows. Figure 11 shows values of $c_{x,t}$ and π_t estimated from the two-parameter-level model.

Table 3: Data periods and estimated μ and σ from the two-parameter-level model

	Singapore	Indonesia	Japan	Korea	Malaysia	E&W
Pre-pandemic Periods	1980 - 2019	1970 - 2019	1970 - 2019	1983 - 2019	1970 - 2019	1970 - 2019
Pandemic Periods ($\mathcal{T}$)	2020 - 2022	2020	2020 - 2022	2020 - 2022	2020 - 2021	2020 - 2022
μ	-0.331	-0.149	-0.275	-0.496	-0.179	-0.189
σ	0.184	0.235	0.253	0.221	0.150	0.226

The estimated values of a_x and b_x from the two-parameter-level model with data up to 2022 are very close to those estimated via the Lee-Carter model with data up to 2019 (see Section 2.3.2), as we expect. The estimated values of k_t from the two-parameter-level model with data up to 2022 also closely follow the trend of k_t estimated via the Lee-Carter model with data up to 2019.

A few observations can be drawn from the parameters estimated:

- The estimated values of π_t are indicative of the magnitude of the overall mortality shock in the COVID-era while the values of $c_{x,t}$ illustrate the variation in mortality shock in each age group. The estimated values of π_t and $c_{x,t}$ can be positive or negative. The complete impact from the COVID-19 mortality shock is quantified by multiplying π_t and $c_{x,t}$. Thus, the direction of age-specific mortality shock should not be interpreted from the sign of π_t or $c_{x,t}$ on a standalone basis, but rather be from the multiple of π_t and $c_{x,t}$, which can be observed from Figure 11. By the same token, the $c_{x,t}$'s associated with a small value of π_t are less meaningful in interpreting the results.

*Figure 11: $c_{x,t}$ and π_t estimated with post-COVID data and the two-parameter-level model**

* In the plot for Japan, π_{2021} is scaled up by a factor of 10 and $c_{x,2021}$'s are scaled down by a factor of 0.1 so that they can fit the plot with other parameters.

- Since a constraint of $\sum_{x=x_1}^{x_m} c_{x,t} = 1$ is imposed on the estimated parameters, the value of $c_{x,t}$ provides indication of the degree of variation in the age specific sensitivity to overall mortality impact related to COVID-19. For example, in Malaysia there is little variation in the age-specific mortality impact relative to the overall mortality shock in 2021, but in 2020, the variation in sensitivity across different age groups is much larger. It is interesting to note that large variation in $c_{x,t}$ is typically associated with very small value of π_t, for example in Malaysia in 2020 and in Japan in 2021. When overall impact of the mortality shock is very small, estimating values of $c_{x,t}$

subject to the constraint of $\sum_{x=x_1}^{x_m} c_{x,t} = 1$ can cause significant noise in the values of $c_{x,t}$.

4.3 Excess Mortality due to COVID-19 Pandemic

Up to this point the focus of this study has been the long-term impact on mortality due to the COVID-19 pandemic. Nevertheless, a statistic of great interest to news media and the general public during the COVID-19 pandemic is the so called "excess mortality". Excess mortality is defined as "the difference in the total number of deaths in a crisis compared to those expected under normal conditions"[4]. It can be calculated according to Equation 3.

Equation 3: Excess Deaths

$$Excess\ deaths\ =\ Reported\ deaths - Expected\ deaths$$

A retrospective evaluation of excess deaths during the COVID-19 pandemic period allows us to learn about the true impact of the pandemic in each country in the past three years. The key to estimating excess deaths is the estimation of expected deaths. However, the question of "How many deaths should we expect to have occurred in the last three years in absence of the pandemic?" is a rather subjective one and is one that we would never find an answer to in the real world. The subjectivity in the number expected deaths can cause variation in the number of excess.

We propose to estimate expected deaths using the Lee-Carter model fitted with recent data. In this section, we explain the rationale behind our proposal, present some empirical evidence supporting it and discuss how we can use the two-parameter-level model to estimate excess deaths under the assumption that the expected deaths follow the Lee-Carter model.

[4] https://www.who.int/data/stories/the-true-death-toll-of-covid-19-estimating-global-excess-mortality

4.3.1 Estimating expected deaths

We choose to use the Lee-Carter model to estimate expected deaths as it captures the dynamics of long-term mortality improvement and is simple to implement. We estimate parameters for projecting expected mortality rates using mortality data from 2010 to 2019 because it reflects the latest trend in mortality. Moreover, we do not require long data periods to reflect the long-term volatility in mortality rates as we are only making short-term forecast of estimating excess deaths in 2020 – 2022.

There are many alternative methods to estimate expected deaths for the purpose of quantifying excess deaths. Identifying the best method among them is beyond the scope of this paper. Nonetheless, we will present some empirical evidence to illustrate the benefit of using our proposed method.

To estimate expected death rates, in addition to using mortality rates predicted by the Lee-Carter model fitted with the previous 10 years' experience, we consider the following three alternatives:

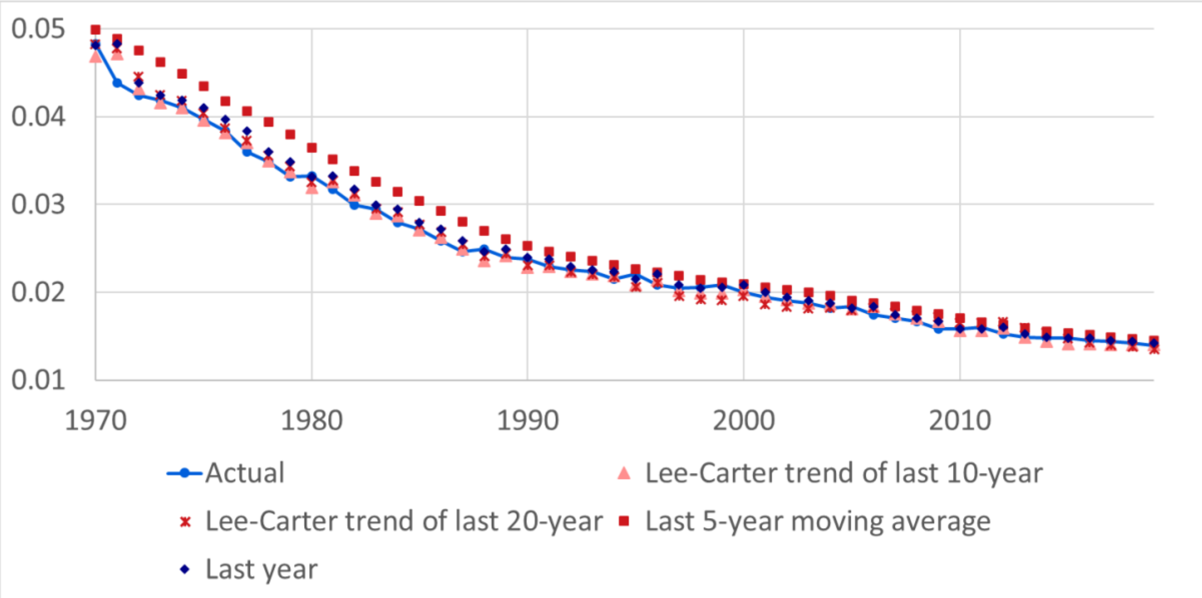
1. Moving average of previous 5 years of mortality rates
2. Last year's mortality rates
3. Mortality rates predicted by the Lee-Carter model which is fitted to the previous 20 years' experience

The use of simple statistics as expected mortality, such as those in the first and second alternative, may seem naïve but is in fact prevalent in many published statistics. For example, the Office for National Statistics in U.K. uses the moving average of previous 5 years as the expected mortality rates[5], while the Ministry of Health in Singapore use the 2019 mortality rates, i.e. last year's mortality rates, as the expected rates (Ministry of Health Singapore, 2022).

[5] https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/deaths/datasets/excessdeathsinenglandandwales

Figure 12 shows the actual mortality rates of age 70-74 in Japan from 1970 to 2019 and compares them with the expected mortality rates calculated with the 4 different methods discussed above. We chose to use the mortality experience for age 70-74 in Japan from 1970 to 2019 as an example because there are sufficient death samples in this group so the data tend to be more stable.

Figure 12: Actual vs. expected death rate. Japan, age 70-74



We calculate the average relative error from the actual mortality rates, which is measured as

$$\frac{1}{n}\sum_{t=t_1}^{t_n}\frac{\left|m_{x,t}^{\text{expected}}-m_{x,t}^{\text{actual}}\right|}{m_{x,t}^{\text{actual}}}$$

of the four estimates of expected mortality rate in the age 70-74 Japan data from 1970-1989, 1990-2019, and 1970 to 2019. The results are summarized in Table 4.

Table 4: Average relative error of expected mortality rates from actual death rates. Japan data for age 70-74 from 1970 to 2019.

Data period	5-year moving average	Last year's rate	Lee-Carter 20-year data	Lee-Carter 10-year data
1970-1989	10.9%	3.7%	2.9%	2.1%
1990-2019	5.8%	2.3%	3.6%	2.4%
1970-2019	7.8%	2.9%	3.3%	2.2%

Table 4 and Figure 12 have shown that the mortality rates predicted by the Lee-Carter model fitted with previous 10 years' data have the best performance in forecasting the actual mortality rates based on the historical data we consider. The performance of using last year's mortality rates as expected comes a close second, while using the 5-year moving average performs far worse than the other three methods. These results are as expected. Using last year's mortality rate as expected mortality can reflect the latest mortality trend, but it is a volatile measure as any volatility in mortality would result in volatility of the expected mortality rate for next year. The 5-year moving average method ignores approximately 3 years' worth of mortality improvement in the expected mortality, which has significant impact particularly in periods where fast mortality improvement is observed. This explains why the deviation from the actual of using the 5-year moving average is the largest during 1970-1989 and has halved during 1990-2019. This result highlights the importance of properly reflecting mortality improvement in the expected mortality calculation.

4.3.2 Estimate excess mortality using various methods

In this section, we demonstrate that the two-parameter-level model can also be used to quantify annual excess deaths during the COVID-19 pandemic by assuming expected deaths follow the Lee-Carter model fitted with data from 2010 to 2019. We then compare excess deaths estimated by the two-parameter-level model with estimates from several widely cited publications.

Recall in the two-parameter-level model in Equation 2, $\log m_{x,t} = a_x + b_x k_t + c_{x,t}\pi_t \mathbf{1}_{t\in\mathcal{T}}$. By definition, $c_{x,t}\pi_t \mathbf{1}_{t\in\mathcal{T}}$ represents the excess log death rates related to the COVID-19 pandemic while $a_x + b_x k_t$ represents the long-term mortality trend we should expect under normal condition. Therefore, we can estimate the excess deaths related to COVID-19 as $E_{x,t}e^{a_x+b_x k_t}\left(e^{c_{x,t}\pi_t \mathbf{1}_{t\in\mathcal{T}}} - 1\right)$. Since we assume expected deaths follow the Lee-Carter model fitted with data from 2010 to 2019, we fit the two-parameter-model with data since 2010 and use the estimated parameters to quantify excess deaths.

It is worth noting that the proposed estimation method for excess deaths is suitable for reviewing the overall mortality impact of the pandemic each year. However, if the focus is on smaller time intervals such as daily, weekly, or monthly excess deaths, which is the case in many other studies, a more complex model is required to reflect the seasonality in deaths within a given year.

The estimates included in the comparison are:

- Zhou & Li model, which is the two-parameter-level model proposed in Zhou & Li (2022), using long-term trend from 2010 and onwards
- WHO: Global excess deaths associated with COVID-19 (modelled estimates) (https://www.who.int/data/sets/global-excess-deaths-associated-with-covid-19-modelled-estimates)
- The Economist: daily estimate of excess deaths around the world (https://www.economist.com/graphic-detail/coronavirus-excess-deaths-tracker)
- Lancet paper: "Estimating Excess Mortality Due to the COVID-19 Pandemic: A Systematic Analysis of COVID-19-Related Mortality, 2020–21." *The Lancet* (Wang et al., 2022)

Appendix C describes the methods used in estimates published by WHO, The Economist and Lancet by Wang et al. (2022).

Figure 13 shows the estimated excess deaths in 2020, 2021 and 2022 of the six countries we consider in this study, where data are available. The numbers are shown in thousands. Note that the Lancet paper sums the excess deaths in 2020-2021 in one number and we show it as the 2021 statistic.

We make several observations about the results in Figure 13:

- There is significant variation in the excess deaths for the same time period estimated by different methods in all countries. Note that in Korea, the WHO and Lancet paper only report estimates up to 2021 so the 2022 estimates in these models are blank.

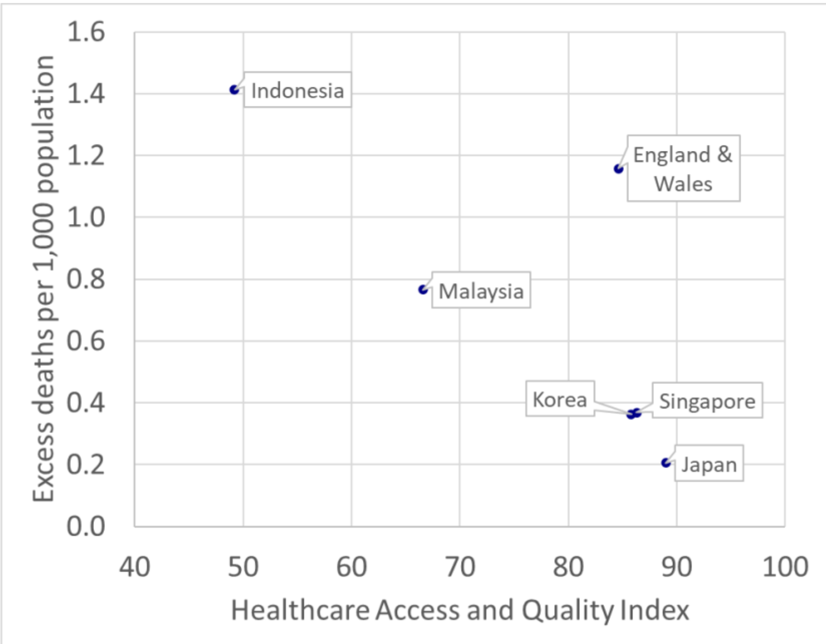
Figure 13: Excess deaths in Singapore, Indonesia, Japan, Korea, Malaysia and England and Wales in 2019-2022. Estimates from difference sources.

- Results produced by the Zhou & Li model are close to the WHO estimates in most cases. This is as expected since the WHO model also captures the secular time trends and the age pattern in mortality that the Zhou & Li model reflects.
- Results from the Lancet paper differ from the other models in many cases, possibly due to the fact that the ensemble model used in this paper does not explicitly adjust for age pattern in mortality rates.

- In countries where the most recent data are not yet available, the Economist estimates an alarming number of excess deaths in 2021 and 2022 in Indonesia, and a moderate number of excess deaths in 2022 in Malaysia. The overall magnitude of excess deaths estimated by the Economist for Malaysia in 2022 is consistent with the 2022 total death count reported by the Department of Statistics Malaysia.

Furthermore, in Figure 14 we plot the average annual excess deaths per 1,000 population in these countries based on the Zhou & Li model, against the Healthcare Access and Quality Index 2015 (Barber et al., 2017). The plot shows an almost linear negative correlation between excess deaths and healthcare accessibility and quality in all countries except England and Wales. A more thorough study of factors impacting excess deaths during the pandemic in all countries will be explored in future work.

Figure 14: Average annual excess deaths per 1,000 population and healthcare access and quality index in each country.



5 Long-term Mortality Impact from COVID-19 pandemic

5.1 Forecasting the long-term trend of mortality improvement

To evaluate the long-term mortality impact from the COVID-19 pandemic, we first need a reasonable forecast of the long-term mortality improvement trend in absence of a pandemic, which is dictated by parameter μ, the drift of the random walk that describes k_t in the two-parameter-level model in Equation 2. More specifically, we need to decide on the value of the drift term μ in the random walk for future projection. This is a complex undertaking in East and Southeast Asian. Unlike developed countries in Europe and North America, where mortality experienced much improvement post World War II and has slowed down since 1970s (United Nations, 2022b), the fast-developing economies in East and Southeast Asia have experienced much steeper mortality improvements in the past few decades. This phenomenon can be observed in the historical age-standardized mortality rates of Japan, Korea and Singapore in Figure 1. Compared to England and Wales, the age-standardized mortality rates of Japan, Korea and Singapore have been declining at a much faster pace. Japan's mortality rates have been running approximately in parallel to England and Wales's rates, but the rate of improvement in Korea and Singapore did not slow down until 2010-2015.

Therefore, it is unreasonable to assume that mortality improvement in fast-developing economies in Asia will continue to be at the same speed as it has been for the past four to five decades, because the room for further improvement in standard of living and access and quality of health care, which are the main factors impacting mortality improvement (Purushotham et al., 2011), is gradually contracting as some of these countries become developed economically.

A study by Wilmoth (1998) examined this very issue for Japan. The author made forecast of life expectancy based on two hypothetical scenarios: one where the exceptionally rapid speed of improvement in life expectancy observed from post-war to the 1990s continues and the other where the speed of improvement in life expectancy converges to the long-term trend of Sweden, a country already achieved the so-called “avant-garde” status in mortality improvement. An “avant-garde” country in this sense is defined as a country “whose overall level of mortality equals the minimum achieved at that time by any national population”. The author suggests that the second scenario is more likely given the few most recent data points available at the time.

In this study, we leverage off the study by Wilmoth (1998) and assume that Japan is now the “avant-garde” country in East and Southeast Asia. In addition, we make the following assumptions about the long-term trend of mortality improvement in absence of any pandemic impact in the countries we study:

- For Japan, Korea, and Singapore, the long-term trend will follow the trend in Japan since 1990, which is what we consider as the “avant-garde” long-term trend in Asia.
- For England and Wales, Indonesia and Malaysia, the long-term trend will follow each country’s own trend since 1970.

The rationale for making such assumptions are as follows. For Japan, we assume it has achieved “avant-garde” status since 1990. This can now be confirmed by actual experience data shown in Figure 15. The period life expectancy at birth in Japan is approximately parallel to that of Sweden since 1990.

For Korea and Singapore, given their rapid mortality improvement in recent decades and the fact that their age-standardized mortality rates have reached Japan’s level before the COVID-19 pandemic, it is reasonable to assume that their trend in mortality improvement will converge to that of Japan. Figure 16 shows the comparison of $e^P_{30,t}$ calculated based on actual mortality rates versus mortality rates following the Japan post-1990 trend in Japan, Korea, and Singapore. For Korea and Singapore, we only compared data points in the 5 years preceding the pandemic since we only expect their experience to start converging to the “avant-garde” long-term trend in the most recent period. Figure 16 shows that the actual experience is better than that projected using the “avant-garde” long-term trend by a very small margin. Despite the small variation, we argue that it is more sensible to assume the "avant-garde" long-term trend in our projection compared to the long-term trend implied by their own experience in the past few decades.

Figure 15: Period life expectancy at birth (data Source: Human Mortality Database)

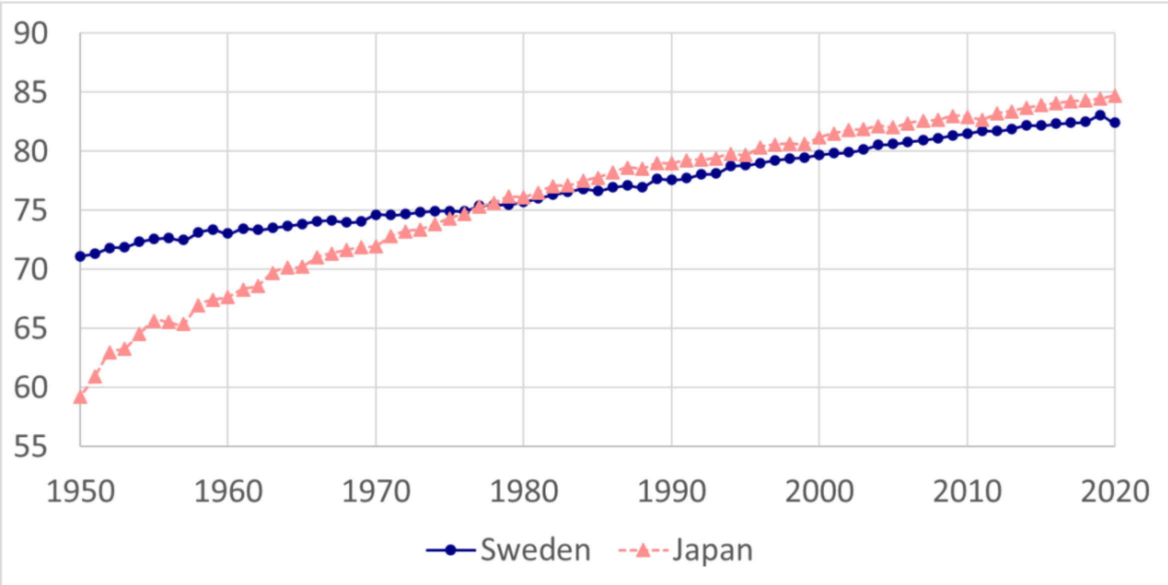
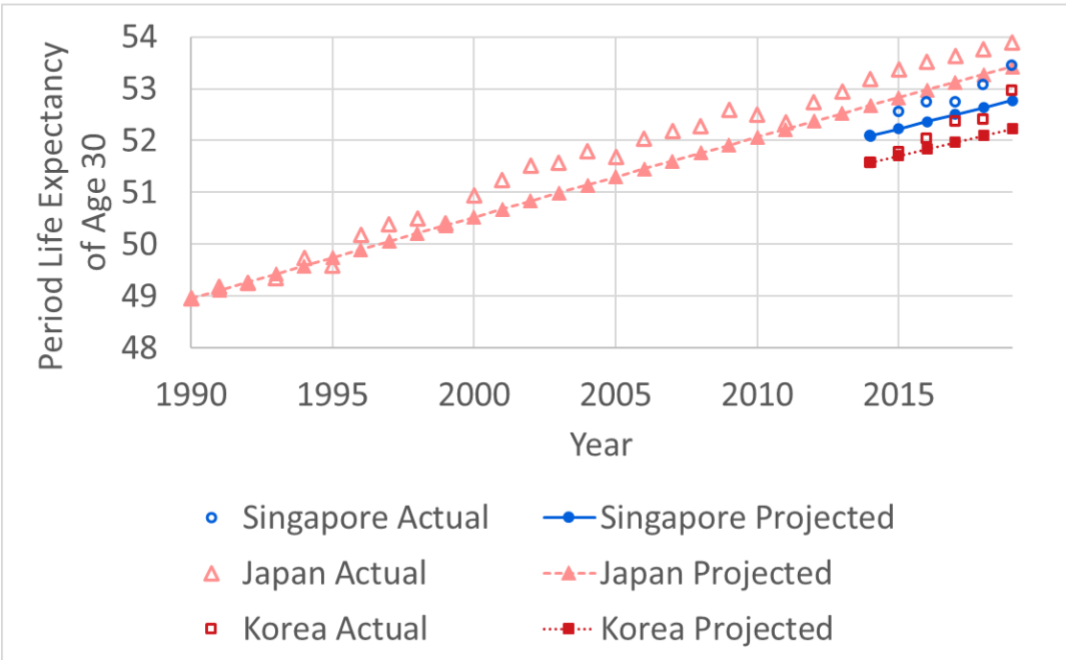


Figure 16: Life expectancy of age 30: Actual and projected using Japan's long-term trend since 1990



For Indonesia and Malaysia, their rate of mortality improvement has been much slower than those observed in countries with faster economic development, and their absolute level of mortality is still much higher than the more developed countries such as Singapore, Japan and Korea. Given an "avant-garde" country is defined as a country whose overall level of mortality equals the minimum achieved at that time by any national population (Wilmoth 1998), we argue that Indonesia and Malaysia have not reached "avant-garde" status in terms of mortality improvement, and there is still much room for their mortality to further improve. Thus, it is reasonable to assume their current trend will continue.

For England and Wales, its mortality experience is rather stable and the trend in mortality improvement since 1970 fits the profile of an "avant-garde" country so we assume such trend will persist.

5.2 Simulation study

Given the stochastic nature of mortality rates and the uncertainty around how the mortality experience will evolve as we enter the endemic phase of COVID-19, we utilize Monte Carlo simulation to forecast the future mortality rates under different scenarios for all countries except Indonesia. Since we only have 2020 data for Indonesia, we conclude it is not credible to make forecast of future mortality in this country based on one-year worth of pandemic data.

5.2.1 Simulation model

The stochastic mortality model we consider for the Monte Carlo simulation is also proposed in Zhou & Li (2022). It is an extension of the two-parameter-level model described in Section 4.1, with additional parameters to reflect the arrival of new pandemic in the future.

Equation 4: Simulation model in general form

$$\log m_{x,t} = a_x + b_x k_t + \sum_i \left(c_{x,t}^{(i)} \pi_t^{(i)} \mathbf{1}_{T_1^{(i)} \le t \le T_k^{(i)}} + c_{x,T_k}^{(i)} \pi_{T_k}^{(i)} \gamma^{g\left(t, T_k^{(i)}\right)} \mathbf{1}_{t > T_k^{(i)}} \right)$$

$$\text{where } \mathbf{1}_t = \begin{cases} 1 \text{ with probability } p \\ 0 \qquad\qquad \text{otherwise} \end{cases} \text{ for any } t > T_k^{(1)}.$$

The parameters in Equation 4 are defined as follows:

- a_x, b_x, and k_t have the same definition as in Equation 2.
- $c_{x,t}^{(i)}$ represents the sensitivity of age x to the overall shock at time t in pandemic i.
- $\pi_t^{(i)}$ reflects the overall impact of the mortality shock in year t of pandemic i.
- For any pandemic i, $c_{x,t}^{(i)} \pi_t^{(i)} \mathbf{1}_{T_1^{(i)} \le t \le T_k^{(i)}}$ describes the mortality shock in the pandemic phase whereas $c_{x,T_k}^{(i)} \pi_{T_k}^{(i)} \gamma^{g\left(t, T_k^{(i)}\right)} \mathbf{1}_{t > T_k^{(i)}}$ describes the mortality shock in the endemic phase, in other words, how the shocked mortality reverses back to normal, if at all.
- γ describes the speed of recovery in mortality to get parallel to its long-term pandemic-free trend again.
- $g(\cdot)$ is a function of t and $T_k^{(i)}$. It takes one of two forms: $g\left(t, T_k^{(i)}\right) = t - T_k^{(i)}$ or $g\left(t, T_k^{(i)}\right) = min(t - T_k, 4)$.

This new model can capture the cumulative impact from multiple pandemic events. The added feature allows us to model the arrival of new pandemics in the future. Additionally, we assume the COVID-19 pandemic between 2019-2022 is pandemic $i = 1$. For $i > 1$, the new pandemic arrives according to a Bernoulli process with a probability of p in any given year.

5.2.2 Simulation scenarios

We forecast future mortality in 6 scenarios. These scenarios are designed to reflect a wide range of trajectories we could expect in future mortality rates with the risk of pandemics taken into consideration, but by no means is this an exhaustive list of how the future mortality may evolve, nor does it represent our expectation of the most likely scenario to occur. Forecasting the most likely trajectory of how mortality under the impact of COVID-19 will evolve requires more data than what is currently available and is beyond the scope of this paper.

The 6 scenarios we consider are described as follows:

- **Scenario 1**: $i = 1,\ p = 0,\ \gamma = 0,\ g\left(t, T_k^{(i)}\right) = t - T_k^{(i)}$.

  The scenario assumes the most recent mortality shock observed in the COVID-19 pandemic disappears completely and immediately, with a full reversion to the pre-pandemic trend. This is the most optimistic scenario. It shows what the mortality rates would have been with no remaining impact after the pandemic years.

- **Scenario 2**: $i = 1,\ p = 0,\ \gamma = 1,\ g\left(t, T_k^{(i)}\right) = t - T_k^{(i)}$.

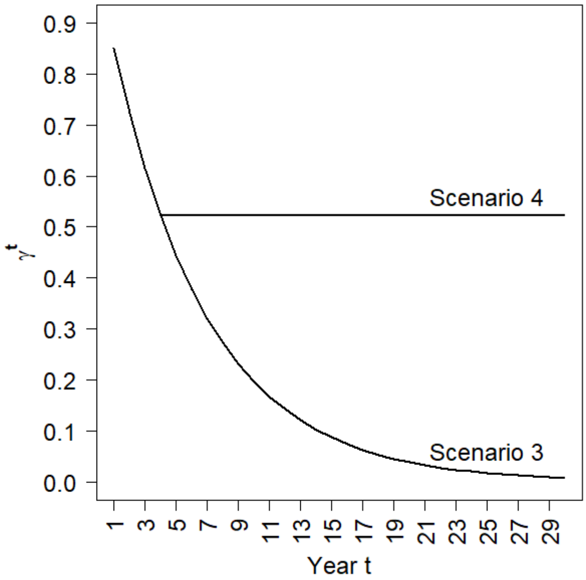
  The scenario assumes the most recent mortality shock observed in the COVID-19 pandemic continues indefinitely and no new pandemic occurs. This is the most pessimistic scenario and is unlikely to materialize in the real world. However, it provides an upper bound of what the mortality rates would be in the coming years given the impact of the COVID-19 pandemic.

- **Scenario 3**: $i = 1,\ p = 0,\ 0 < \gamma < 1,\ g\left(t, T_k^{(i)}\right) = t - T_k^{(i)}$.

  The scenario assumes the most recent mortality shock observed in the COVID-19 pandemic subsides indefinitely according to a power function, and no new pandemic occurs. We use $\gamma = 0.85$ in the simulation results shown in Section 5.2.4, which implies that the mortality shock in the log death rates $\log m_{x,t}$ will be reduced to about 50% by year 4, 10% by year 14 and 1% by year 28. Figure 17 illustrates values of the power function in Scenario 3 and 4 with $\gamma = 0.85$.

  This is a more reasonable outlook for mortality rates. It reflects a situation of gradual recovery in mortality improvement, in which the virus becomes less fatal to human being, for example with better therapeutics, more effective vaccines, built-up herd immunity in the population, and more efficient health care system. In this model, the speed of recovery in mortality improvement is dictated by the parameter γ, and can vary substantially depending on the value of γ.

Figure 17: Illustration of power function γ^t with $\gamma = 0.85$.



- **Scenario 4**: $i = 1,\ p = 0,\ 0 < \gamma < 1,\ g\left(t, T_k^{(i)}\right) = min(t - T_k, 4)$.

  The scenario assumes the most recent mortality shock observed in the COVID-19 pandemic subsides only for 4 years according to a power function, and no new pandemic occurs. Value of the power function with $\gamma = 0.85$ is again illustrated in Figure 17. This is a more adverse scenario than Scenario 3. It leaves a permanent gap in mortality level from what it would have been without the pandemic. The size of the gap depends on how much the mortality can recover in 4 years after the pandemic, which is again dictated by the parameter γ. The choice of a normalizing period of 4 years is rather arbitrary. Since the pandemic has already persisted for 3 years, we assume the reversion back to the pre-pandemic trend of mortality improvement will take slightly longer and pause after 4 years. This assumption can be revisited once more data become available.

- **Scenario 5**: $i \geq 1$, $p = 0.01$, $0 < \gamma < 1$, $g\left(t, T_k^{(i)}\right) = t - T_k^{(i)}$.

  The scenario assumes the most recent mortality shock observed in the COVID-19 pandemic subsides indefinitely according to a power function, and a new pandemic occurs with a probability of p each year. Note that we assume it is possible for new pandemic to arrive before the previous one runs its course. The impact from each pandemic will be added to impact from the previous pandemic(s) in this case. Furthermore, we assume that once a new pandemic occurs, its impact on mortality is of the same magnitude and lasts for the same duration as the COVID-19 pandemic. This is a very strong assumption but without the support of more data and evidence, it is not worse than any other assumption.

- **Scenario 6**: $i \geq 1$, $p = 0.05$, $0 < \gamma < 1$, $g\left(t, T_k^{(i)}\right) = t - T_k^{(i)}$.

  This scenario is identical to Scenario 5 except the new pandemic will be five times as likely to occur in any given year as in Scenario 5.

5.2.3 Simulation parameters

We use parameters estimated in Section 4.2 for each country in this simulation study, with the exception of μ for Japan, Korea and Singapore. As discussed in Section 5.1, for these three countries, we assume $\mu = -0.203$, which is the μ estimated from the two-parameter-model using the Japan data from 1990-2021. Note this μ suggests a slower rate of mortality improvement than what is shown in Table 3 in Section 4.2 due to the different data periods used in estimation. This is to avoid being over-optimistic about the rate of mortality improvement in future.

Furthermore, the simulation requires estimated values of parameters $c_{x,t}$ and π_t for $t = T_1, \ldots, T_k$, where $T_1 = 2020$, $T_2 = 2021, T_3 = T_k = 2022$. For Malaysia, since we only have data up to 2021, we assume that $c_{x,2022} = c_{x,2021}$, and $\pi_{2022} = 0.8 \times \pi_{2021}$. The multiplier of 0.8 is estimated based on the total deaths count reported for 2021 and 2022 in Malaysia by their Department of Statistics.

As discussed in Section 5.2.2, we choose $\gamma = 0.85$ in the simulation. This is a rather conservative assumption. However, by examining the data from England and Wales, where the most amount of mortality impact is available in the countries we consider, a factor of $\gamma = 0.85$ is justifiable as the England and Wales data suggest only a very small improvement in the mortality shock in 2022 compared to 2021. We choose to estimate γ based on the experience of England and Wales because among the countries we study, only England and Wales have three years' experience with large mortality impact during the pandemic, from which we can observe how mortality evolve year over year after the first major wave of deaths.

For parameter p which governs how fast new pandemics arrive in Scenario 5 and 6 outlined in Section 5.2.2, we set $p = 0.01$ in Scenario 5 and $p = 0.05$ in scenario 6. In scenario 5, $p = 0.01$ corresponds to the assumption that a pandemic of similar scale to COVID-19 would occur at a rate of 1 in 100 years. This is consistent with the fact that the last pandemic with similar impact is the 1918 influenza pandemic, 101 years prior to the COVID-19 pandemic. In scenario 6, $p = 0.05$ corresponds to the assumption that a pandemic of similar scale to COVID-19 would occur at a rate of 1 in 20 years. This is a more aggressive assumption but considering it has been less than 20 years between the SARS outbreak in 2003 and the COVID-19 pandemic in 2019, the assumption is still plausible.

5.2.4 Simulation results

In each of the five countries we consider for forecasting via simulation and for each scenario outlined in Section 5.2.2, we conduct $N = 10{,}000$ Monte Carlo simulations of the log central death rates $\log m_{x,t}$ for $t = 2023, \ldots, 2120$, x corresponds to each quinquennial age group above age 30 and up to the maximum age in the mortality data. We then interpolate $m_{x,t} = exp(\log m_{x,t})$ between age groups, extrapolate them to a limiting age of $\omega = 120$, and convert each $m_{x,t}$ into $q_{x,t}$, which is the probability that an age x in year t dies in the next year. After that, we use $q_{x,t}$ to calculate the indices we are interested in. The algorithm for simulating $\log m_{x,t}$, converting them to $q_{x,t}$ and calculating indices are illustrated in Appendix B.2.

The indices we are interested in are:

- Period life expectancy of an age 30 and age 65, respectively: $e^{P}_{30,t}$ and $e^{P}_{65,t}$ for $t = 2019, \dots, 2052$.
- Cohort life expectancy of an age 30 and age 65 in year t, respectively: $e^{C}_{30,t}$ and $e^{C}_{65,t}$ for $t = 2022, 2030$.

We choose to show life expectancy of an age 30 as it reflects the mortality of adult ages; we choose to show life expectancy of an age 65 to illustrate impact on the retired population.

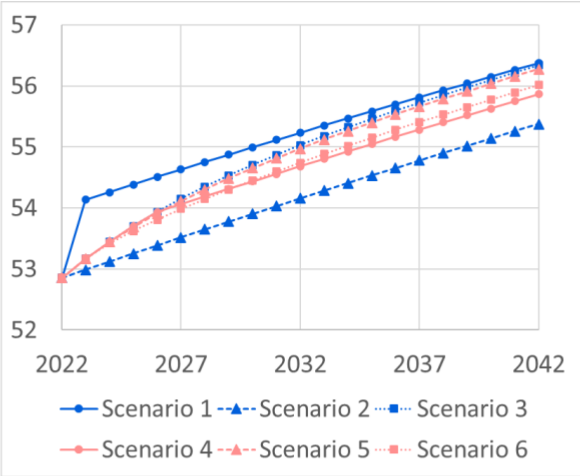
Note that in the Monte Carlo simulation, each scenario for each country uses the same sequence of random numbers. This is to avoid additional variance in results across scenarios and countries that could arise purely due to the different random numbers used in simulation.

5.2.4.1 Period life expectancy

Figure 18 shows a 20-year projection of the *mean* of the simulated period life expectancy at age 30 and age 65, respectively, in the 6 simulation scenarios described in Section 5.2.2 for Singapore. The figure illustrates how life expectancy evolves in the next 20 years in each scenario so that we can build a concrete idea of the impact on life expectancy in different scenarios on an expected value basis. We only show the data for Singapore since all countries share similar shape of the trajectory of life expectancy in each scenario, with only the absolute level of life expectancy and the deviation between scenarios differ by country.

In Figure 19 and Figure 20, we also show the boxplot of simulated period life expectancies of an age 30 and age 65, respectively, in year 2032, of all 5 countries in all 6 scenarios. The boxplot provides a fuller picture of the range of outcomes in each of the simulated scenarios.

Figure 18: Projected period life expectancy of age 30, $\boldsymbol{e^{P}_{30,t}}$, (left panel) and age 65, $\boldsymbol{e^{P}_{30,t}}$, (right panel) in Singapore. Data shown are the mean life expectancy in the Monte Carlo simulation.



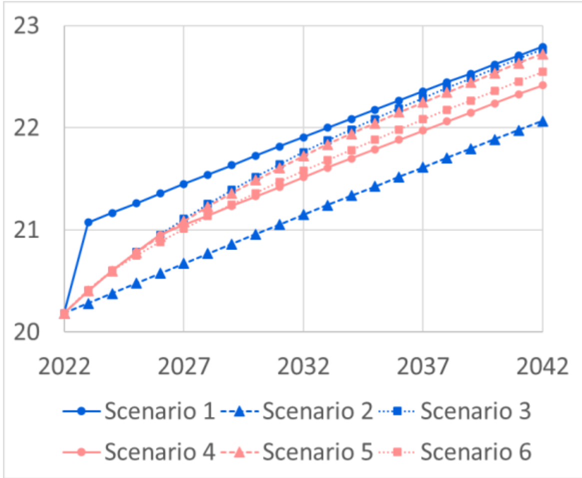


Figure 19: Boxplot of period life expectancy $e^{P}_{30,2032}$

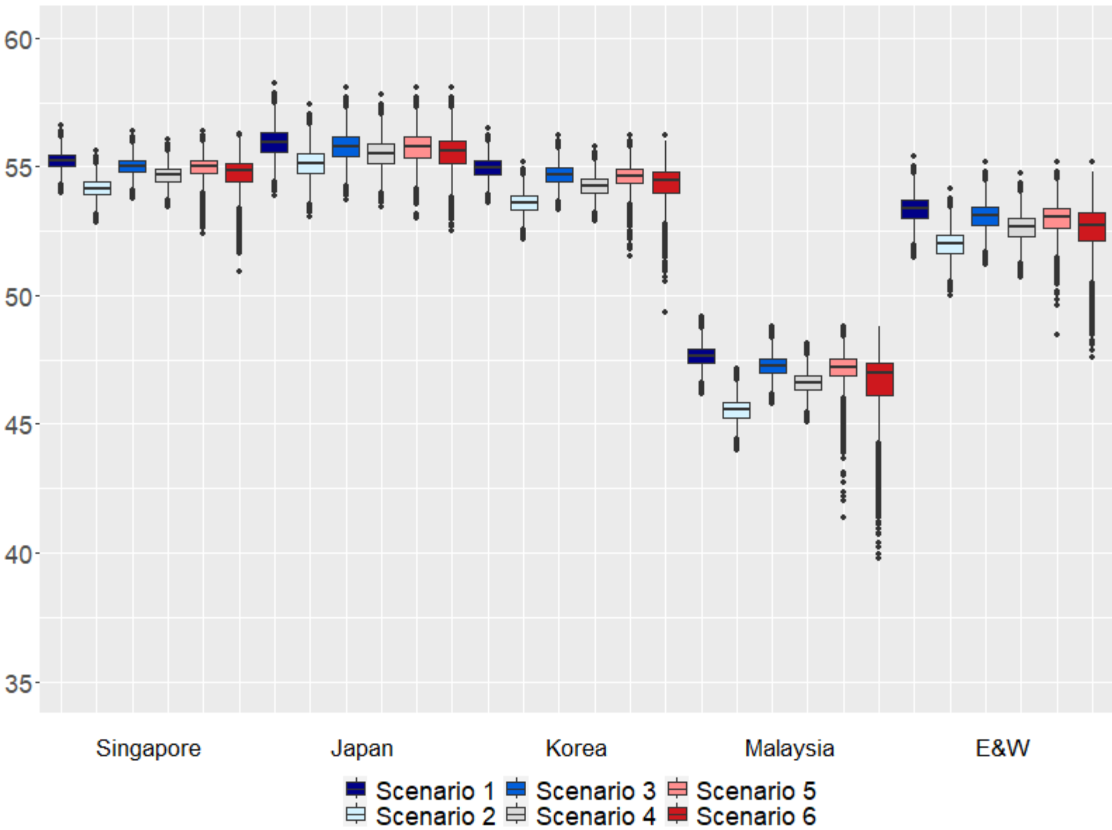
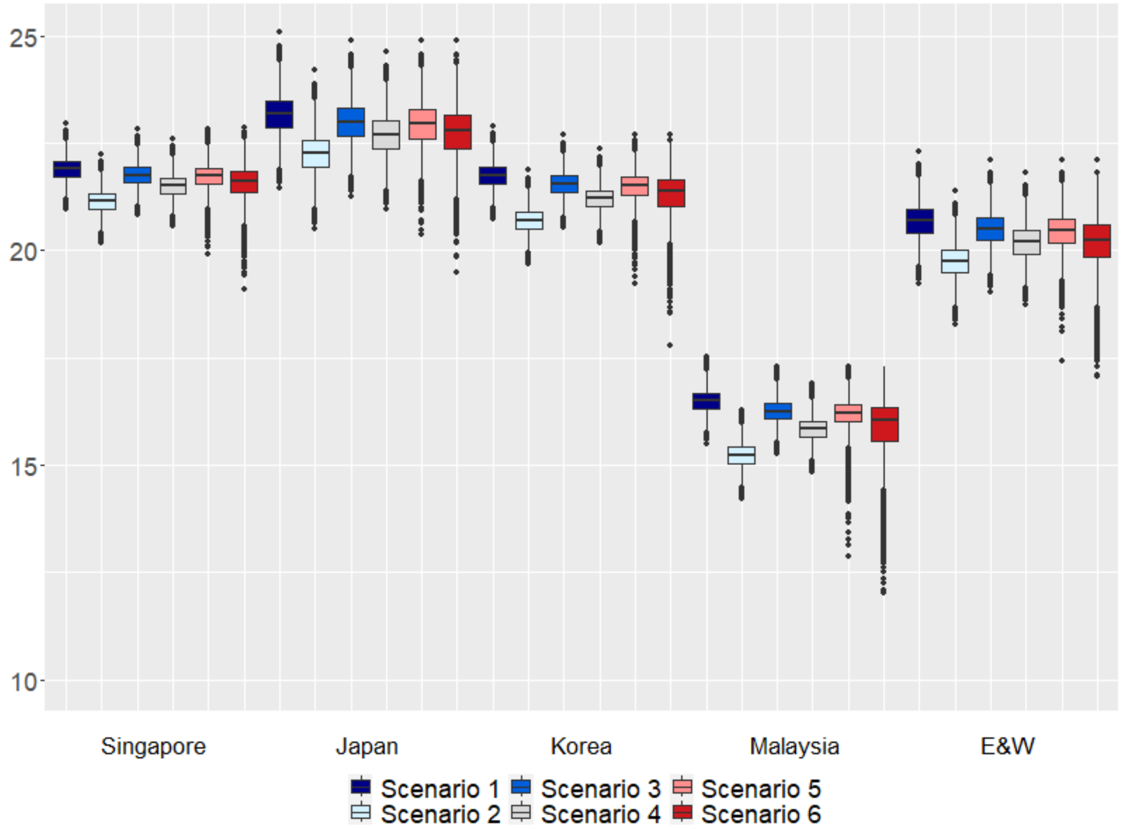


Figure 20: Boxplot of period life expectancy $e^P_{65,2032}$



Overall, the period life expectancies at both age 30 and age 65 observe similar pattern across different scenarios in any given country. We make the following remark about these results.

- In any given country, the deviation in life expectancy between different scenarios are consistent with the country's magnitude of mortality shock during the pandemic.
- In Scenario 5 and 6, even though their mean life expectancies are both very close to that of Scenario 3, the simulation result shows significant left tail risk (lower life expectancy) in these two scenarios. The left tail risk is even more pronounced in Scenario 6, which is consistent with its assumption of higher probability of new pandemic arrival.
- In any given country, $e^P_{65,t}$ tends to have a larger variance than $e^P_{30,t}$. This is as expected because for $e^P_{30,t}$, with a longer projection horizon, the drift term μ

of the random walk process that describes mortality improvement dominates the outcome of projection more so there is less random variation.

- In any given country, the first and third quartile of outcome in Scenario 3 to 6, represented by the upper and lower edge of the box, are within the data range of Scenario 1, the scenario representing pre-pandemic mortality level. This suggests that Scenario 3 to 6 are indeed possible scenarios given the long-term historical volatility. Nonetheless, this should not be interpreted as reason not to be concerned about the impact from these scenarios since the left tail risks shown in Scenario 3 to 6 are substantial.

Figure 21 and Figure 22 illustrate how many years it will take for the period life expectancy to get back to the 2019 level in each country under each of the 6 scenarios. The variation in results among different scenarios in each country is commensurate with the set-up of the scenario and the mortality impact experienced in each country. It takes Malaysia particularly long to reverse to pre-pandemic level due to its bigger mortality impact during the pandemic and its slow speed of mortality improvement in the long-term mortality trend.

Figure 21: Year post COVID-19 pandemic in which $e^{P}_{30,t}$ gets back to $e^{P}_{30,2019}$

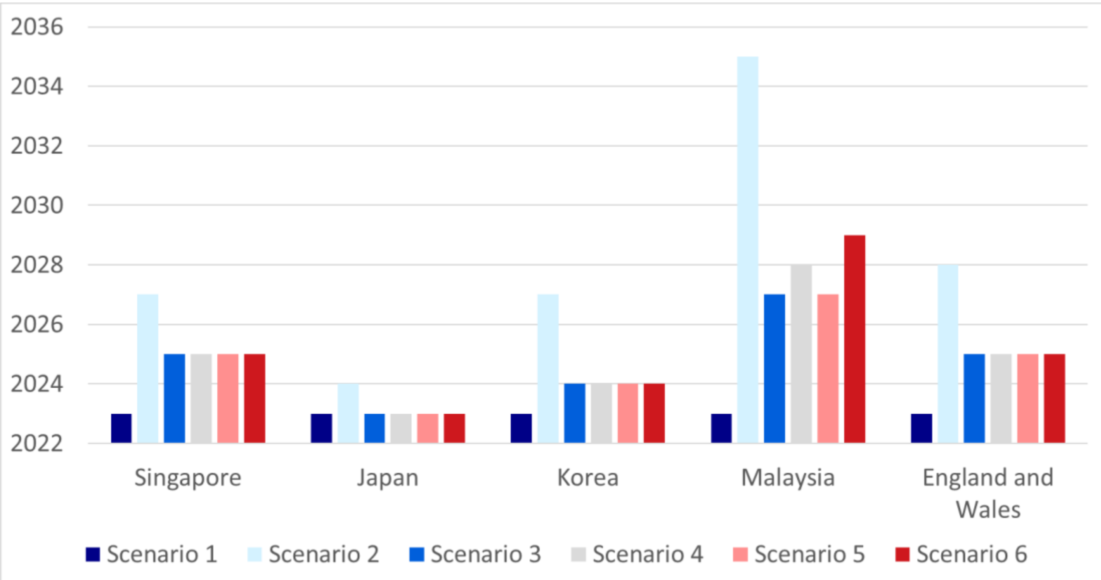
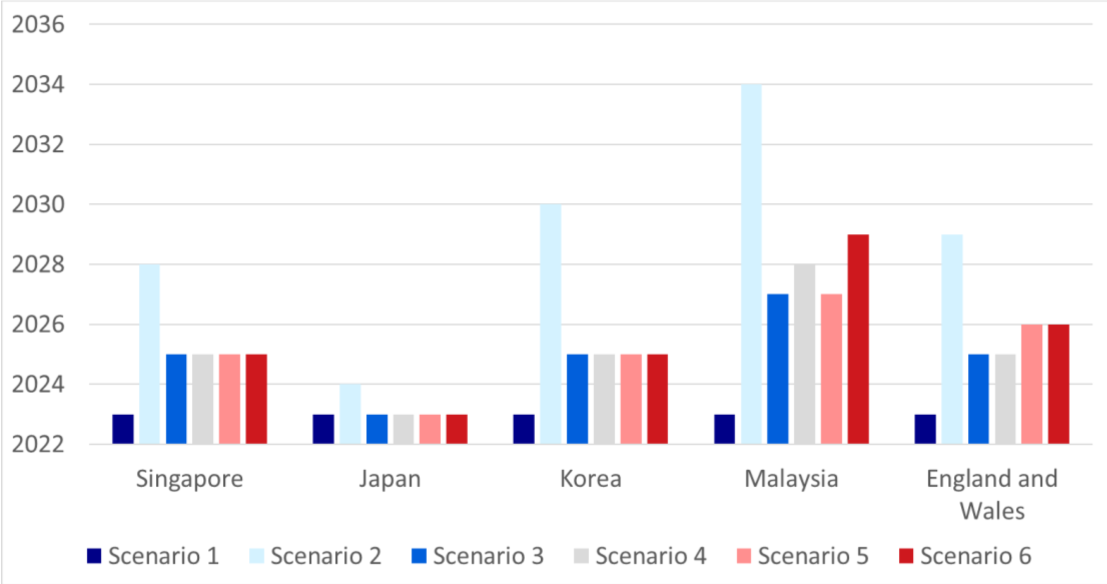


Figure 22: Year post COVID-19 pandemic in which $e^{P}_{65,t}$ gets back to $e^{P}_{65,2019}$



5.2.4.2 Cohort life expectancy

In Figure 23 to Figure 26, we plot boxplots for each of the simulated cohort life expectancy of an age 30 in 2022 and 2032, and of an age 65 in 2022 and 2032.

We make the following observations from these boxplots:

- There is much smaller variation in cohort life expectancy among different scenarios in all countries, compared to the period life expectancy because the impact of the pandemic will be diluted by future mortality improvement (OECD, 2023)
- There is higher uncertainty around cohort life expectancy compared to period life expectancy because it accumulates the stochasticity in mortality rates over a much longer period, until the cohort reaches limiting age. It is also the reason why $e^{C}_{30,t}$ has larger variance than $e^{C}_{65,t}$.
- In all scenarios, an age 30 in Japan in 2022 is expected to live beyond age 90, with Singapore and Korea quickly catching up in 2032. This signals substantial longevity risk in these countries in the future.

Figure 23: Cohort life expectancy $e^{C}_{30,2022}$

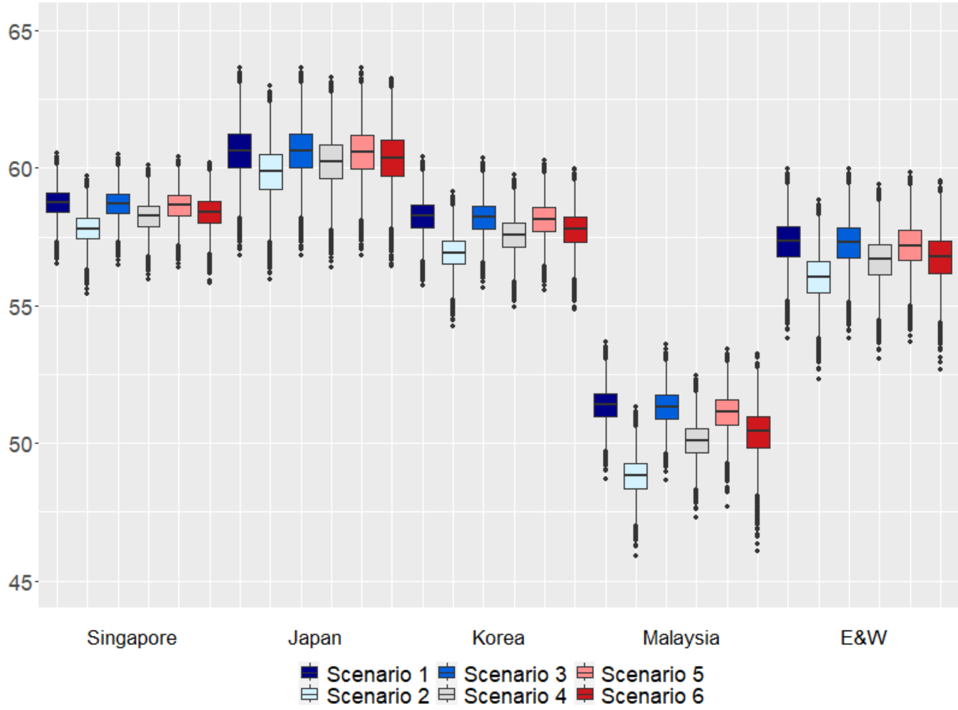


Figure 24: Cohort life expectancy $e^{C}_{30,2032}$

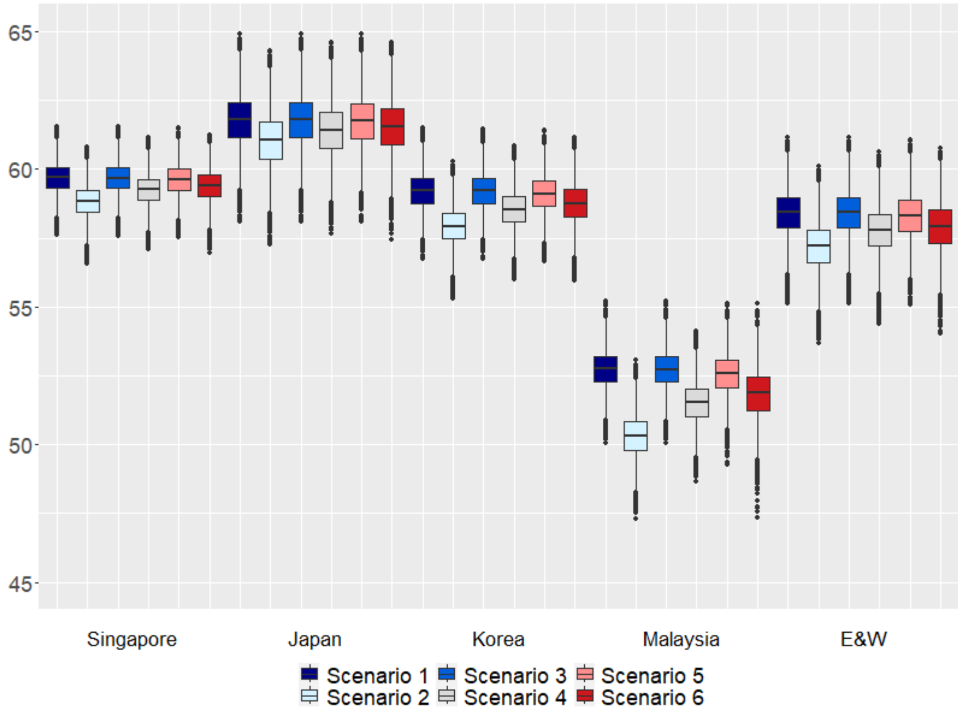


Figure 25: Cohort life expectancy $e^{C}_{65,2022}$

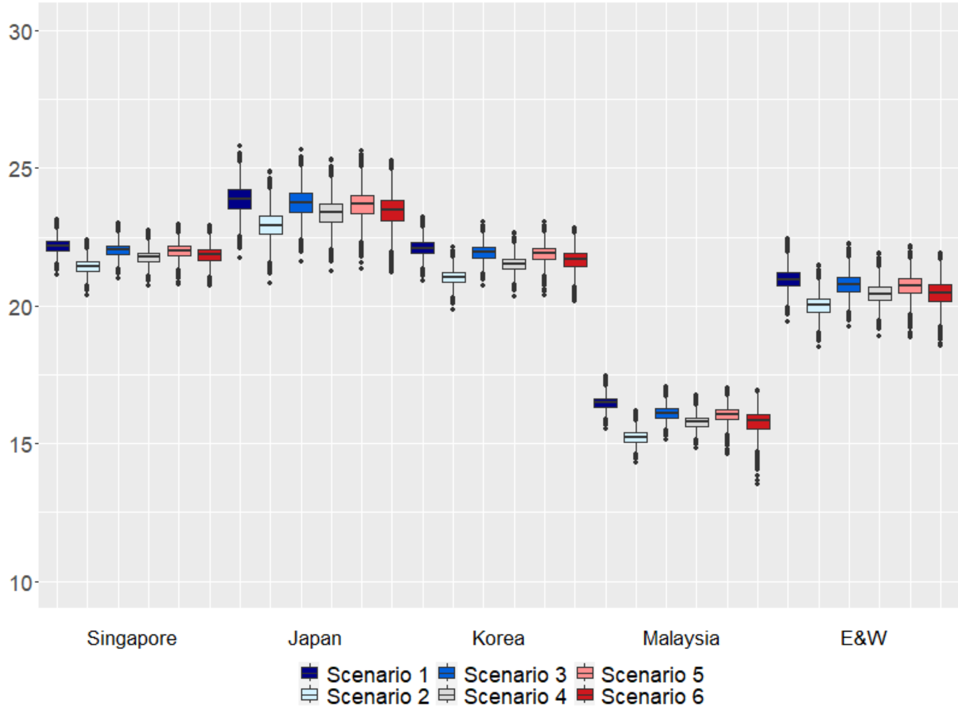
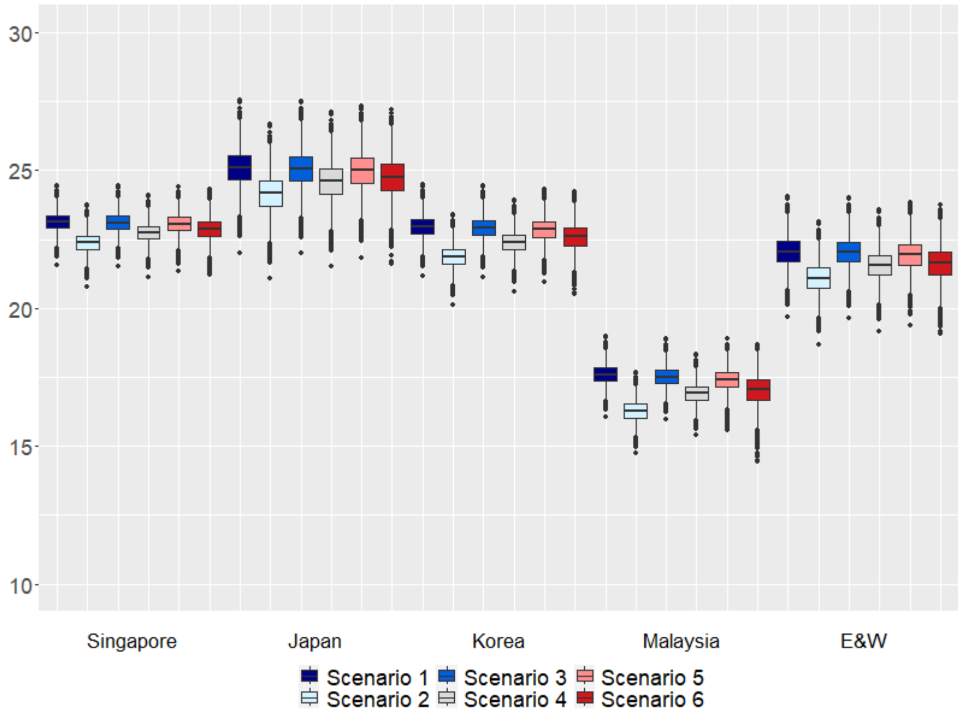


Figure 26: Cohort life expectancy $e^{C}_{65,2032}$



6 Implications and Recommendations

In this section, we present our recommendations to life insurance practitioners and policymakers based on the analysis and observations from this study.

6.1 Mortality experience monitoring and data collection

We have demonstrated in this study great variation in mortality experience among the six countries we considered in terms of

- Long-term mortality experience such as
  - Overall level of mortality rates, which is the *value* of mortality rates
  - Level of mortality improvement, which is the *first derivative* of mortality rates with respect to time t
  - Trend in the level of mortality improvement, which is the *second derivative* of mortality rates with respect to time t

- Short-term mortality shock such as
  - Magnitude and direction of mortality shock by time during the COVID-19 pandemic
  - Magnitude and direction of mortality shock by age group during the COVID-19 pandemic

Unlike a long-developed economy like England and Wales, the characteristics of long-term mortality experience listed above can change very rapidly in the developing or recently developed countries in Asia. Thus, it is crucial to closely monitor the mortality experience in this region, promptly quantify the impact of recent development and make changes to business practice, strategies, and public policies accordingly.

With all the machine learning technologies available today, it would be very beneficial for insurance companies and governments to build infrastructure that can facilitate conversion of historical data into standardized format and timely collection of new mortality data with high degree of granularity. This will enable timely and insightful data analysis with the help of machine learning techniques. One of the challenges we faced in this study is the lack of up-to-date data that reflects the latest trend in mortality during the COVID-19 pandemic.

One unique feature of East and Southeast Asia is that the life insurance industry only starts to take off in recent decades in many regions. Building and utilizing proper data infrastructure with the latest technology from this early stage could benefit life insurers in these new markets tremendously in the long run.

In addition to timely collection of data, we also encourage industry participants to be more open minded about sharing their experience data with organizations that have research capacity such as the Global-Asia Insurance Partnership and academia. A large, robust, suitably de-identified and frequently updated collective dataset could provide valuable insight for all participants in the life insurance industry. Admittedly data security and data privacy are of paramount importance, but proper data governance practice should reduce the risk of data breach to a minimum.

6.2 Mortality modelling

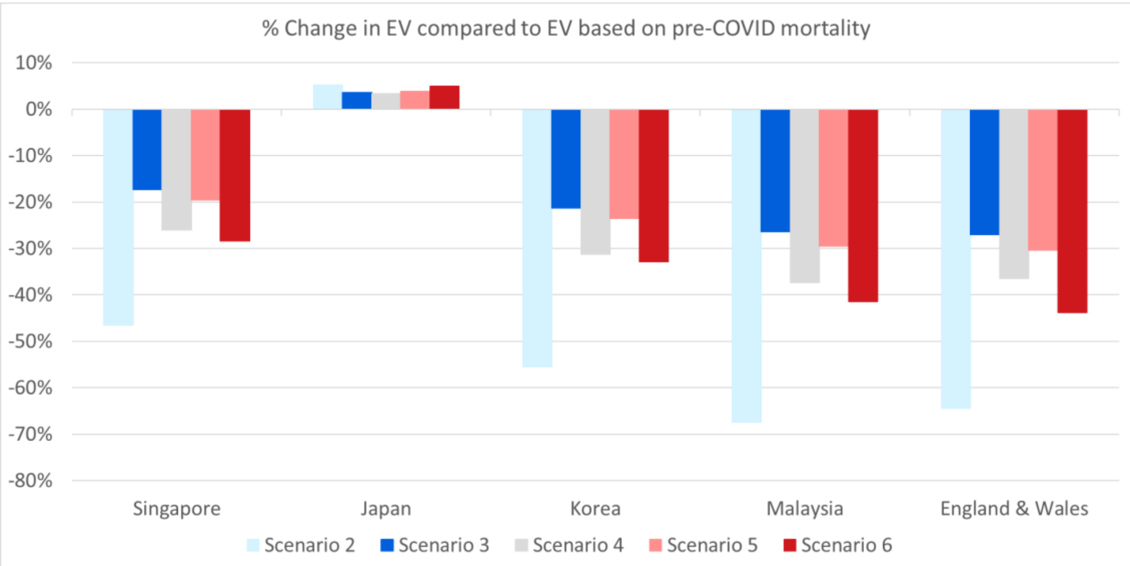
In terms of modelling the impact of mortality shock from the COVID-19 pandemic, the two-parameter-level model presented in this study is a useful tool for this purpose. Despite some of its limitations discussed in Section 4.1, the model is quite powerful in accurately capturing the age and period specific impact of the mortality shock, and its results are easy to interpret. The estimation of model parameters is also straight-forward to implement.

Insurance companies and pension schemes can use the two-parameter-model to evaluate the mortality impact of the pandemic in their existing portfolio. They can also use extensions of the model to make forecast of future mortality rates, similar to the simulation study done in this report. The model's use case can also be extended to modelling other major but temporary mortality shocks, for example from natural disasters or wars.

6.3 Risk management

As we have shown in the simulation results, the pandemic has resulted in mortality regressing by a number of years' worth of mortality improvement in all countries we consider, some more than others. For in-force life insurance contracts with guaranteed level premium, particularly the mortality sensitive products that are priced competitively such as term life insurance, the mortality impact could greatly hinder the profitability of the product. We use a simplified example of a term-20 life insurance portfolio to illustrate this point. Figure 27 shows the change in Embedded Value (EV) for the term life portfolio in each scenario we consider in Section 5.2.2 compared to the EV calculated with pre-pandemic mortality. The assumptions for the EV calculation can be found in Appendix D.

Figure 27: Percentage change in EV in each scenario compared to EV based on pre-COVID mortality



The EV comparison shows that the financial impact can be quite significant in countries with substantial mortality impact from COVID. On the other hand, for in-force products with longevity risk such as annuities or pension schemes, we could expect some mortality gain until the mortality experience recovers and catches up to long-term trend. Because the pandemic related mortality impact varies by country and by age group, companies should pay close attention to their product mix and business risk mix. For example, in all scenarios for Japan, the EV calculation shows a small gain because Japan actually had small improvement in mortality for age 45-65 during the pandemic. For pandemic mortality sensitive life insurance products, companies should maintain a diversified portfolio and avoid being overweight in regions and age groups that are most negatively impacted.

Given the above, we strongly encourage life insurance companies to review the EV impact under different scenarios of pandemic-related mortality shocks in their own portfolios, and to incorporate such mortality scenarios as part of their risk management practices. We are sharing a set of tools as electronic supplement material of this report with partners of Global Asia Insurance Partnership via the members-only section of their website at www.gaip.global. Life insurance practitioners can refer to these tools for mortality stress-testing of their book of business. Appendix E provides more details about the electronic supplementary material.

Further, it is also important to incorporate the excess mortality insights and other learnings from the COVID-19 pandemic into scenario analyses and stress testings. For life insurance players who had already been incorporating pandemic or epidemic scenarios in their analyses, it is recommended that learnings from COVID-19 be taken into account to update those scenarios and stresses, and for those who did not have a pandemic or epidemic scenario in their analyses and stress testings to start incorporating such scenarios, in order to keep refining on their risk management and analyses practices. In a similar vein, regulators and supervisors are encouraged to start incorporating pandemic or endemic scenarios in their scenario analyses and stress testing as part of the prudential management requirements, or for those who already has such requirements to look into updating the requirements around such scenarios.

In this study, we focus on quantifying the immediate mortality impact of the COVID-19 pandemic and forecasting a few possible scenarios of how the mortality experience might return to its normal trend. One potentially significant risk factor that could distort the trajectory of returning to normal is the long-term impact on mortality due to COVID-19 infection. For example, Xie et al. (2022) conducted a study using a national healthcare databases from the US Department of Veterans

Affairs and concluded that the risk and 1-year burden of cardiovascular disease in survivors of acute COVID-19 are substantial, and the risk and burden increase for those who are more severely ill during the acute COVID-19 infection. How many of the excess cardiovascular disease incidence will eventually lead to excess deaths is unclear at this point, but companies and policymakers should also be aware of this risk factor and closely monitor the emerging mortality experience in the next few years.

Looking into the future, companies and governments should remain vigilant about the next new pandemic even though the world has transitioned to the endemic phase of the COVID-19 pandemic. The lessons we learn from this study that could help better manage mortality risk in the next pandemic include:

- Life insurance companies to consider maintaining a more diverse portfolio of products, to manage the risk of adverse impact due to another pandemic.
- Life insurance companies to be more aware of the risks of concentration in specific age groups of the population in their portfolio.
- Improving accessibility and quality of healthcare to the population will definitely help countries weather the next pandemic better, and hence, we recommend governments to seek to improve accessibility and quality.

Aside from the pandemic, we have observed in the data analysis that substantial longevity risk is present in the developed economies in this region such as Japan, Korea and Singapore. As shown in Figure 23, an age 30 in 2022 in Japan is expected to live for another 60 years approximately. By 2032, an age 30 in Singapore and Korea will also be expected to live beyond age 90. Insurers, pension sponsors and policymaker should not lose sight of this glaring longevity risk in spite of the COVID-19 pandemic.

6.4 Protection gap

Our findings highlight several insurance protection gaps in East and Southeast Asia, some of which have been exacerbated by the COVID-19 pandemic. We discuss the gaps in mortality, longevity, and healthcare protection in this section.

6.4.1 Mortality protection gap

We discussed that in all countries except Japan, relative to their mortality rates under normal circumstances, the younger age groups (age 35-50) suffered more than the older age groups (age 65+), even though the absolute mortality rates of younger age groups are still much lower than that of older age groups during the pandemic. This is particularly true in the less developed economies like Malaysia and Indonesia. Despite the much smaller number of deaths in these younger age groups, this is the part of the population in their prime wage-earning years. They are also the population group with a lot of financial responsibility in terms of supporting dependents. Therefore, deaths at these younger ages are much more likely to cause financial hardship for the family of the deceased.

According to Swiss Re Institute (2020), the mortality protection gap, defined as "the difference between the protection needs of a household and the financial resources available to sustain a family's future living standards in the event of the premature death of the main breadwinner(s)" is between 70-75% in Indonesia and Malaysia. If the COVID-19 mortality impact were to persist, or if another pandemic with similar mortality impact were to prevail, the protection gap in these middle-aged adults will become more damaging. Governments in these countries could consider policies that may help close the mortality protection gap.

6.4.2 Longevity protection gap

As we have shown in Figure 2, in all the Asian countries we have considered in this study, their mortality experience have achieved great improvement in the past few decades. Additionally, according to Figure 23 and Figure 24, a thirty-year old in 2022 in Japan is expected to live to age 90 in almost all 6 future scenarios we have considered with the pandemic impact taken into account. Meanwhile a thirty-year old in 2022 in Singapore or Korea is not far behind that in Japan in terms of life expectancy. The long life expectancies in the developed economies in this region could mean significant gap in longevity protection in the next few decades. The situation is particularly grim considering the extremely low birth rates in these countries, which means fewer labour force in the economy and less tax revenue that could be relied upon to support social security programs.

6.4.3 Health protection gap

Although in this study we have not formally studied the impact of COVID-19 on healthcare provision and accessibility, or any correlation between healthcare accessibility and mortality, we have shown some evidence on the disparity of healthcare accessibility and quality among the countries we consider and how such disparity is correlated with disparity in excess mortality. Thus, it is beneficial to expand protection for healthcare in this region and improve healthcare accessibility.

Overall, the COVID-19 pandemic has led to implications across a few protection gaps. A holistic, multi-stakeholder, approach to managing protection gaps, as suggested in GAIP's paper, "About the Protection Gap", will be more efficient and effective. Interested readers may find the paper on GAIP's website[6].

6.5 Morbidity impact

In this study, we have illustrated the impact COVID-19 has on mortality. Meanwhile, the disease has also had large impact on morbidity. Compared to the number of deaths, the virus has caused many more people to be moderately or severely ill, to the extent that they require hospitalization and other medical treatments. Moreover, the strain on the healthcare system during the peak of the pandemic has resulted in many people avoiding or delaying care, similar to the points we raise in Section 3.1, which has led to sicker patients and more expensive treatment when they eventually get the care they require. Additionally, more and more medical research, for example Al-Aly et al. (2021), has shown that virus can cause damage in multiple systems in human bodies, and will worsen health status in the long run, which will take up healthcare resources.

[6] https://www.gaip.global/publications/about-the-protection-gap/

Despite the material impact, there are very few publicly available morbidity data that we could use to assess the morbidity experience during the COVID-19 pandemic. We encourage insurers to study the morbidity impact in their book of business as it pertains to health insurance, critical illness and disability income insurance. We also welcome governments and insurers to collaborate and share data with us to study the morbidity impact of COVID-19.

7 Limitations

Despite our effort in finding reliable mortality data and suitable model to study and forecast the mortality impact from the COVID-19 pandemic, limitations remain in the findings of this study. For example,

- This study is based on the data available in early 2023. Indonesia only has data available up to 2020 whereas Malaysia does not have detailed death data for 2022. For Singapore, Japan, Korea and E&W, their mortality data in 2022 are still provisional and their final 2022 mortality data will almost surely differ from the provisional data we use. Therefore, the mortality impact estimated in this study will change once all final data become available.
- Despite the strengths of the two-parameter-model that we discussed in Section 4.1, the model still suffers from some shortcomings. For example, the model assumes that mortality shock during the pandemic is deterministic and will be identical in future pandemics in terms of how the mortality shock varies by age and how it evolves during the course of the pandemic. This assumption is highly simplistic since we can almost be certain that the next pandemic will be different. For example, the 1918 pandemic caused most deaths in younger population rather than the older population (Pearce et al., 2011). However, we do not have the data and evidence to make claims about how the mortality impact from future pandemics will differ from COVID-19. In addition, the model does not capture the cohort effect in the long-term mortality trend.
- The method to estimate excess mortality using the two-parameter-level model is useful for quantifying annual excess deaths, but to quantify excess deaths over smaller time intervals such as months or weeks, we suggest using a more sophisticated model to adjust for the significant seasonality in the distribution of deaths within a year.
- This study is based on the population mortality data, rather than the insured lives' mortality data. We caution against making direct inference about the mortality experience in the insured population from the conclusion of this study. It is a well-established fact that the mortality rates of the insured

population are lower than the general population, due to selection effect of the underwriting process and generally better socioeconomic status of the insured population (Dickson et al., 2019). Moreover, evidence also points to correlation between socioeconomic factors and COVID-19 related mortality (Hawkins et al., 2020). Early study done by Rick Leavitt (2021) shows much lower death rates in the group life population than the general population, after simple adjustment for age-sex distribution. In addition, given the variability in mortality experience we observe in this study, it is reasonable to assume that the relationship between the pandemic mortality impact of insured and general population also varies from country to country.

- As discussed in Section 6.5, this study focuses on mortality impact during the COVID-19 pandemic. Morbidity impact also has significant implication for life insurers and policymakers but is outside the scope of this study.

8 Conclusion

East and Southeast Asia is a vast region with highly dense population, different levels of economic development, and diverse culture and political system. Understandably the mortality experience during the COVID-19 pandemic also vary from country to country. In this study, we examine the mortality impact during the COVID-19 pandemic for five countries in this region closely. We identify that some countries and subgroups of the population are more severely impacted by the pandemic than others, but overall, the pandemic has wiped out several years of mortality improvement for all these countries.

We attempt to make some forecasts on the trajectory of mortality after the pandemic, but how mortality will return to its normal trend in real life remains to be seen. The life insurance industry and policymakers should closely monitor the evolution of mortality experience, identify parts of the portfolio vulnerable to negative mortality outcome, and actively manage the mortality risk in their portfolio from COVID-19 as an endemic and from any new pandemic that may arise.

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A. Mortality Data Source and Modification

Table 5 summarizes the source and time periods of the mortality data we collect for each country to facilitate this study.

Table 5: Data period and data source in the mortality database

Country/Territory	Data Period	Data Source
Singapore	1980 - 2022	Singapore Department of Statistics
Indonesia	1970 - 2020	UN World Population Prospects (WPP) 2022
Japan	1970 - 2022	Human Mortality Database (HMD) Statistics of Japan
Korea	1983 - 2022	Korean Statistical Information Service (KOSIS)
Malaysia	1970 - 2021	UN World Population Prospects (WPP) 2022 Department of Statistics Malaysia
England & Wales	1970 - 2022	Human Mortality Database (HMD) Office for National Statistics, UK

We prioritize data from the Human Mortality Database, followed by national statistical offices, while considering data from the World Population Prospects as a last resort. The Human Mortality Database is a reliable source of historical data that is widely used in mortality studies in actuarial research. The World Population Prospects is also a reliable source, but many adjustments and smoothing techniques have been applied to its data, in order to unify the data format and data coverage, and to follow a unified analytical protocol for all countries considered (United Nations, 2022a). The smoothing and adjustments tend to remove some short-term fluctuations in the mortality experience which are important to stochastic mortality modelling.

In addition, we summarize in Table 6 modifications made to the data from these sources. These modifications are made to close small gaps in the data so that we can make full use of the latest information available. They are built upon some underlying assumptions. Moreover, the 2022 data in Japan, Korea and E&W are provisional. As the final data become available in the future, they are highly likely to deviate from the provisional data and the assumptions we made, which will lead to different estimated parameters in our model and different mortality forecast. However, we do not expect the deviation to be material.

Table 6: Data modifications

Country/Territory	Modification
Singapore	In 1981-1989, the last age group in the original data is 75+. For this period, we modify the data such that deaths and population in age group 75-79, 80-84, 85+ are split based on linear interpolation of their respective mix between 1980 and 1990.
Indonesia	None
Japan	For 2022, we use the Statistics of Japan data. Only the first 11 months of deaths and population estimates are available at the time this report is prepared. We prorate the first 11 months of deaths data by a factor of 12/11 to arrive at the 2022 annual deaths. The 2022 exposure are estimated as the average of the first 11 months' population estimates. We also calculate the deaths and exposure for 2021 from the Statistics of Japan data in a similar fashion. We then apply the ratio of 2022 death rate over 2021 death rate based on the Statistics of Japan data to the 2021 death rate in the HMD data to arrive at the 2022 death rate. This is consistent with the two-parameter-level model (Equation 2) in which the mortality impact during the COVID-19 pandemic is modelled as a multiplier to mortality rates following the long-term mortality trend.
Korea	Exposure between 1983 and 2002 in age groups above 80 are in aggregate in original data. They are split based on the age group mix in the WPP data. For 2022, we use the 2022 KOSIS provisional data, which show death data by decennial age groups. We assume that the ratio between the death rate of 2021 and 2022 in any quinquennial age group is the same as such ratio in the corresponding decennial age group. Based on this assumption, we solve the death rate for each quinquennial age group in 2022.
Malaysia	In 1970-2019, WPP data are used. In 2020-2021, the Department of Statistics data were used to reflect the latest and most verifiable mortality data after the pandemic. More specifically, the ratio between the death rates in 2020-2021, relative to 2019 in the Department of Statistics data, were

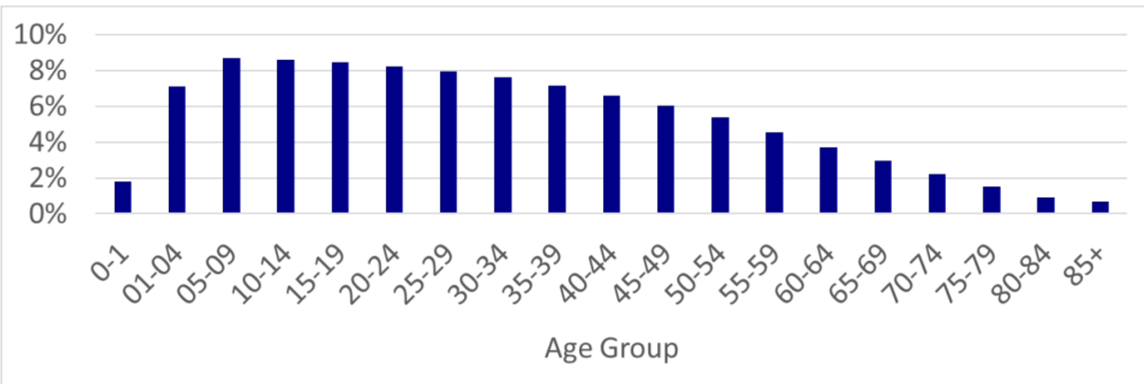
	applied to the 2019 death rates in WPP data to arrive at the 2020-2021 death rates used in this study.
England and Wales	In 1970-2020, HMD data are used. The 2021-2022 death data and 2021 exposure data are from Office of National Statistics (ONS). The HMD data and the ONS data are highly consistent. The 2022 exposure data are calculated from the 2021 exposure by adding the population aged from the previous year and subtracting the population passed away during the year. We assume deaths occurred uniformly throughout the year.

In terms of data period, the World Population Prospects include data for all countries listed above since as early as 1950, while mortality data for England and Wales in the Human Mortality Database date back to 1800s. However, we only included data in and after 1970 because many data in these Asian countries prior to 1970 appear to have poor quality. In addition, given the fast economic development in Asia in recent decades, we do not consider mortality experience prior to 1970 relevant to forecasting future mortality trend.

We include England and Wales in this study for comparison, because it is a developed economy and has endured significant mortality impact from the COVID-19 pandemic which provides sufficient data points for comparison.

Figure 28 shows the age mix in the WHO standard population (Ahmad et al., 2001) used for calculating age-standardized mortality rates in Section 2.1 and 3.3.

Figure 28: Age mix in the WHO standard population.



B. Estimation and Simulation of the Two-Parameter-Level Model

Recall the two-parameter-level model described in Equation 2 Section 4.1, where the log central death rates are modelled as:

$$\log m_{x,t} = a_x + b_x k_t + c_{x,t} \pi_t \mathbf{1}_{t \in \mathcal{T}}$$

Here k_t follows the random walk with drift such that

$$k_t = k_{t-1} + \mu + \epsilon_t, \qquad \epsilon_t \overset{i.i.d.}{\sim} N(0, \sigma^2)$$

and $\mathbf{1}_{t \in \mathcal{T}}$ is an indicator function with a value of 1 if $t \in \mathcal{T}$ and 0 otherwise.

Furthermore, given a set of mortality data from ages $x_1, \dots, x_m$ and year $t_1, \dots, t_n$, the following constraints are imposed to the model:

$$\sum_{x=x_1}^{x_m} b_x = 1, \qquad k_{t_1} = 0, \qquad \sum_{x=x_1}^{x_m} c_{x,t} = 1.$$

In this section, we document the process of estimating parameters a_x, b_x, k_t, $c_{x,t}$, π_t, μ, and σ in model using historical data and the algorithms of the simulation study discussed in Section 5.2.

B.1. Estimation of two-parameter-level model

We use mortality data described in Section 2 and estimate the central death rate $m_{x,t}$ as $m_{x,t} = \frac{D_{x,t}}{E_{x,t}}$, for $x = x_1, \dots, x_m$ and $t = t_1, \dots, t_n$.

According to Zhou & Li (2022), under the assumption that $D_{x,t}$ follows a Poisson distribution with a mean of $E_{x,t} m_{x,t}$, the two-parameter-level model can be written as a generalized linear mixed model (GLMM) with a Poisson distribution for the response variable and a logarithm link function. Furthermore, Zhou & Li (2022) pointed out that according to Breslow & Clayton (1993), the estimates of the mean parameters $\boldsymbol{\theta} = \{a_x, b_x, k_t, c_{x,t}, \pi_t, \mu\}$ in this GLMM can be obtained by maximizing the quasi-likelihood function (PQL).

In the two-parameter-level model, let $\boldsymbol{k}$ denote the vector $[k_{t_2}, k_{t_3}, \dots, k_{t_n}]'$. Then $\boldsymbol{k}$ follows a multivariate normal distribution with mean vector

$$\boldsymbol{\mu} = [\mu, 2\mu, \dots, (n-1)\mu]'$$

and a variance-covariance matrix $\boldsymbol{V}$, where the (i,j)-th entry of $\boldsymbol{V}$ is

$$\boldsymbol{V}_{ij} = (\min(i,j) - 1)\sigma^2.$$

Then the joint probability density function of $\boldsymbol{k}$, denoted by $f(\boldsymbol{k})$, is

$$f(\boldsymbol{k}) = (2\pi)^{-\frac{n-1}{2}} |\boldsymbol{V}|^{-\frac{1}{2}} e^{-\frac{1}{2}(\boldsymbol{k}-\boldsymbol{\mu})' \boldsymbol{V}^{-1}(\boldsymbol{k}-\boldsymbol{\mu})}$$

where $|\boldsymbol{V}|$ is the determinant of the matrix $\boldsymbol{V}$.

The PQL function of the model is

$$g(\boldsymbol{\theta}) = \sum_{x,t} \left(D_{x,t} \log m_{x,t} - E_{x,t} m_{x,t} \right) - \frac{1}{2} (\boldsymbol{k}-\boldsymbol{\mu})' \boldsymbol{V}^{-1} (\boldsymbol{k}-\boldsymbol{\mu})$$

$$= \sum_{x,t} \left(D_{x,t} (a_x + b_x k_t + c_{x,t} \pi_t \mathbf{1}_{t \in \mathcal{T}}) - E_{x,t} e^{a_x + b_x k_t + c_{x,t} \pi_t \mathbf{1}_{t \in \mathcal{T}}} \right) - \frac{1}{2} (\boldsymbol{k}-\boldsymbol{\mu})' \boldsymbol{V}^{-1} (\boldsymbol{k}-\boldsymbol{\mu})$$

After substituting the mean parameters $\boldsymbol{\theta} = \{a_x, b_x, k_t, c_{x,t}, \pi_t, \mu\}$ by their estimated values, the variance parameter σ can then be obtained by maximizing the following approximate profile quasi-likelihood function:

$$h(\boldsymbol{\theta}, \boldsymbol{\sigma}) = -\frac{1}{2} \log |\boldsymbol{V}| - \frac{1}{2} \log \left| -\frac{d^2}{d\tilde{\boldsymbol{k}}^2} g(\tilde{\boldsymbol{\theta}}, \boldsymbol{\sigma}) \right| + g(\tilde{\boldsymbol{\theta}}, \boldsymbol{\sigma})$$

The procedure for estimating the parameters is outlined in Algorithm 1. It is an iterative process using Newton's method to maximize the penalized quasi-likelihood and the approximate profile quasi-likelihood.

Algorithm 1: Parameter Estimation in the Two-Parameter-level Model

initialize: Initialize parameter values as

1. Set $a_{x_{prev}}$ = estimated a_x using the Lee-Carter model;
2. Set $b_{x_{prev}} = c_{x,t_{prev}}$ = estimated b_x using the Lee-Carter model;
3. Set $k_{t_{prev}} = \pi_{t_{prev}}$ =estimated k_t using the Lee-Carter model;
4. Set μ_{prev} = estimated μ using the Lee-Carter model;
5. Set σ_{prev} = estimated σ using the Lee-Carter model;
6. $\delta = \eta = 1$;
7. Update $g_{prev}(\boldsymbol{\theta}) \leftarrow g(\boldsymbol{\theta})$;
8. Update $h_{prev}(\boldsymbol{\theta}) \leftarrow h(\boldsymbol{\theta})$;

while $\delta > 0.0001$ **do**

  while $\eta > 0.0001$ **do**

    for $\theta \in \{a_x, b_x, k_t, c_{x,t}, \pi_t, \mu\}$ **do**

$$\text{Update } \theta_{curr} \leftarrow \theta_{prev} - \frac{\frac{\partial}{\partial\theta} g(\theta_{prev})}{\frac{\partial^2}{\partial\theta^2} g(\theta_{prev})}$$

    end

    Update $\eta = g(\boldsymbol{\theta_{curr}}) - g_{prev}(\boldsymbol{\theta})$

    Update $\boldsymbol{\theta}_{prev} \leftarrow \boldsymbol{\theta}_{curr}$

    Update $g_{prev}(\boldsymbol{\theta}) \leftarrow g(\boldsymbol{\theta_{curr}})$

  end

$$\text{Update } \sigma_{curr} \leftarrow \sigma_{prev} - \frac{\frac{\partial}{\partial\sigma} h(\sigma_{prev})}{\frac{\partial^2}{\partial\sigma^2} h(\sigma_{prev})}$$

  Update $\delta = h(\sigma_{curr}) - h_{prev}(\sigma)$

  Update $\sigma_{prev} \leftarrow \sigma_{curr}$

  Update $h_{prev}(\sigma) \leftarrow h(\sigma_{curr})$

end

In the two-parameter-level model, the penalized quasi-likelihood estimation methodology is superior to the traditional two-stage estimation method for estimating parameters in the Lee-Carter model. The penalized quasi-likelihood estimation methodology can isolate the impact from the pandemic shock of $c_{x,t}\pi_t \mathbf{1}_{t\in\mathcal{T}}$ from the long-term mortality trend captured by k_t. The heuristic behind the phenomenon is that the PQL method penalize any deviation from the multivariate normal distribution that we assume k_t's are conformed to. Interested readers may refer to Zhou & Li (2022) for more detailed discussion on the methodology of penalized quasi-likelihood estimation, its better estimation result compared to the two-stage estimation method in Lee-Carter model and why that is the case.

B.2. Simulation using a multi-parameter-level model

Given the estimated parameter values, we simulate mortality rates and various mortality indices for each country according to Algorithm 2.

Algorithm 2: Simulating mortality rates and mortality indices from the two-parameter-level model

input: Estimated values of a_x, b_x, k_{t_n}, c_{x,t_n}, π_{t_n}, μ, and σ ;

N: number of simulation samples;

T: number of years to forecast in simulation;

initialize: Set $\boldsymbol{\mu} = [\mu, 2\mu \ \dots, T\mu]$;

Set the (i, j)-th entry of the $T \times T$ variance-covariance matrix V to be $\boldsymbol{V}_{ij} = (\min(i, j) - 1)\sigma^2$;

for $i = 1$ to N **do**

Randomly sample $\boldsymbol{z_i}$ from $MVN(\boldsymbol{\mu}, V)$

Set $\boldsymbol{k_i} = [k_{t_n+1}, k_{t_n+2}, \dots, k_{t_n+T}]' = k_{t_n} + \boldsymbol{z_i}$;

Compute $\log m_{x,t}$ for $t = t_n + 1, \dots, t_n + T$;

Compute $q_{x,t}$ for $t = t_n + 1, \dots, t_n + T$;

Compute mortality indices for $t = t_n + 1, \dots, t_n + T$;

end

The computation for $\log m_{x,t}$ was done according to Equation 4 and each scenario described in Section 5.2.2.

The computation for $q_{x,t}$ involves several steps:

Step 1: Extrapolate $m_{x,t}$ from the maximum age in the mortality data to the limiting age of 120 using the Kannisto method (Thatcher et al., 1998). This is consistent with the method used in the Human Mortality Database (Wilmoth et al., 2007).

Step 2: Linearly interpolate $m_{x,t}$ between each age group into single age.

Step 3: Apply Whittaker gradation (Whittaker, 1922) to smooth $m_{x,t}$ in each age.

Step 4: Calculate q_x from m_x as

$$q_x = \begin{cases} \dfrac{m_x}{1+(1-a_x)m_x}, & for\ x = 0, 1, \cdots, 119 \\ 1, & for\ x = 120 \end{cases}$$

where $a_x = \frac{1}{2}$ for all x.

The Step 4 calculation of $q_{x,t}$ is according to the basic lifetable calculation in Wilmoth et al. (2007). Normally a unique a_x will be used when $x = 0$ to account for the empirical distribution of deaths in the first year of life. However, since we focus on mortality rates and indices for age 30 and above in this study, we will use $a_0 = \frac{1}{2}$ for simplicity.

The mortality indices we are interested in are calculated as follows:

$$e_{x,t}^{P} = \sum_{s=1}^{\omega-x} {}_{s}p_x$$

$$e_{x,t}^{C} = \sum_{s=1}^{\omega-x} \prod_{u=0}^{s-1} p_{x+u,t+u}$$

C. Methodology for Calculating Excess Deaths

We describe the methodologies used for calculating excess deaths during the COVID-19 pandemic in the several studies mentioned in Section 4.3. In particular, we focus on how the expected deaths and actual deaths are treated in each study.

C.1. WHO: Global excess deaths associated with COVID-19

Reference: Msemburi et al. (2023)

Results from the WHO study are published in Msemburi et al., (2023) while a detailed documentation of methodology can be found in WHO, (2022). The estimated excess deaths data in this study can be found in https://www.who.int/data/sets/global-excess-deaths-associated-with-covid-19-modelled-estimates.

In this study, the expected deaths are estimated using a generalized linear model (GLM) with negative binomial link function. The mean of the distribution is modelled as a yearly trend component plus a so called within-year component which accounts for seasonal variation. Both the yearly trend and within-year trend are modelled through spline functions. In cases where monthly mortality data are unavailable, temperatures are used as a proxy for monthly mortality variation.

In countries where no mortality data are available, a Bayesian approach is used to estimate actual death counts. An over-dispersed Poisson log-linear regression model is used, with the link function taking into account covariates such as COVID-19 death rate, test positivity rate, and containment measures. Variation due to gender and age pattern are also taken into consideration in the estimation.

C.2. The Economist: The pandemic's true death toll

Reference: The Economist (2021)

The methodology used to model the excess mortality in the excess mortality tracker published by the Economist is documented in (Solstad, 2021). The estimated excess deaths data can be accessed via https://github.com/TheEconomist/covid-19-excess-deaths-tracker while the code and input data can be accessed via https://github.com/TheEconomist/covid-19-the-economist-global-excess-deaths-model.

According to the document, the excess mortality is predicted by a modelled trained via a gradient boosted tree model using a large number of variables. The excess deaths data for training the model are collected from external sources.

C.3. The Lancet: Estimating excess mortality due to the COVID-19 pandemic

Reference: Wang et al. (2022)

In this study, the expected deaths are estimated via an ensemble of 6 models. The first 4 models are variation of a two-level model. Both parts of the two-level model are Poisson regression model, where the mean is based on a linear spline function. The first level captures the seasonality in death counts and is estimated first. Then based on the first level estimates, the second level reflects the secular time trend in death counts. The variations between the 4 models are in where the knots are placed in the spline function. The fifth model in the ensemble is a Poisson regression model, but the seasonality and secular time trend are modelled simultaneously. The sixth model simply assumes that the expected deaths for 2020 and 2021 are the same as in the same week of 2019. For countries where actual deaths are unavailable, the excess deaths are predicted using a linear model where the covariates are determined via the Least Absolute Shrinkage and Selection Operator (LASSO) regression performed on countries where actual deaths are available.

D. Assumptions in EV Example

Product description

	Description
Product	Term-20 life insurance
Issue age	45
Issue date	1/1/2018
Sum insured	1,000,000
Premium	Singapore: 3,000; Indonesia: 11,000 Japan: 3,600; Korea: 3,250 Malaysia: 7,450; England and Wales: 3,850
Sales commission	75% of first year premium

Assumption

	Pricing Assumption	Valuation Assumption	Solvency Assumption
Interest rate	4.5%	3.5%	3.0%
Inflation	3.0%	2.0%	2.0%
Acquisition expense	500	500	500
Maintenance expense	200	220	240
Lapse rate	2.5% in policy year 1-5; 5.0% thereafter	2.0 % in policy year 1-5; 4.0% thereafter	1.25% in policy year 1-5; 2.5% thereafter
Mortality rate	Simulated mortality rates in Scenario 1-6 in Section 5.2.2	Simulated mortality rates in Scenario 1-6 in Section 5.2.2 with 10% MfAD	Simulated mortality rates in Scenario 1-6 in Section 5.2.2 with 20% MfAD

- EV valuation date: December 31, 2022
- For simplicity, we assume no basis change in any scenario.
- Premiums are calculated based on pricing assumptions and an IRR of approximately 10% for all countries.

E. Electronic Supplementary Material

We are sharing a set of tools as electronic supplementary material to support the utilization of models and findings in this study by practitioners. The tools we share are:

a) R code for estimating parameters of the two-parameter-level model from mortality data, and for simulating mortality rates under the 6 scenarios we consider in Section 5.2.2
b) 10,000 paths of simulated central death rates for 60 years in quinquennial age groups under each of the 6 scenarios
c) The ratios between each simulated central death rate in b) and the 2022 mortality rates in each respective age group

Table 7 is an excerpt from the ratios we provide for item c). In this table, we provide the ratio of the simulated central death rates and the 2022 central death rate in Singapore for age group 65-70, in 1 out of the 10,000 Monte Carlo (MC) simulation sample paths under each scenario.

We suggest users to apply the R code to fit a two-parameter-level model using their own mortality data and simulate mortality rates, subject to the limitations we discussed in Section 7 when using the two-parameter-level model and the proposed simulation scenarios.

Users may also apply the ratios we provided in c) to their own mortality rates in 2022 to arrive at new sample paths of mortality rate projection. However, this approach should only be used as a **last resort** if users are interested in testing the **relative** mortality impact in their own book of business under different scenarios, but do not have the capacity to utilize the R code. This is **not** our recommended approach to quantify mortality impact of COVID-19 because the simulated rates are based on population data in each country we study, which reflect the long-term mortality trend of the specific data period, and the mortality impact during the COVID-19 pandemic from 2020-2022. Unless the mortality experience of the population of interest happens to be identical to the one we have studied, there will be inconsistency between the mortality rates simulated by the actual stochastic mortality model in R and the mortality rates generated by applying the ratios in c).

Table 7: Excerpt of ratios between simulated central rates and the 2022 mortality rates in Singapore for age group 65-70

Year	Scenario 1 MC sample 1	Scenario 2 MC sample 1	Scenario 3 MC sample 1	Scenario 4 MC sample 1	Scenario 5 MC sample 1	Scenario 6 MC sample 1
2023	0.81056	0.97385	0.94741	0.94741	0.94741	0.94383
2024	0.83842	1.00732	0.95730	0.95730	0.95730	0.93843
2025	0.82847	0.99536	0.92731	0.92731	0.92731	0.90401
2026	0.81053	0.97381	0.89202	0.89202	0.89202	0.85124
2027	0.80764	0.97034	0.87616	0.88884	0.87616	0.82831
2028	0.79993	0.96107	0.85726	0.88035	0.85726	0.80570
2029	0.79549	0.95574	0.84370	0.87547	0.84370	0.78338
2030	0.78510	0.94325	0.82536	0.86403	0.82536	0.76673

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