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COVID-19 RISK MAPPING AND LIFE INSURANCE ESTIMATION: MARKOV CHAIN MODEL FOR PREMIUMS AND BENEFITS IN BANDUNG CITY

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ABSTRACT

The COVID-19 pandemic, first identified in China, rapidly spread worldwide and significantly impacted various sectors, including health and insurance. In Indonesia, regional disparities in case trends have highlighted the need for localized risk assessment. This study applies a Markov Chain model to estimate life insurance premiums and benefits by forecasting long-term COVID-19 transmission probabilities across 30 sub-districts in Bandung City. The analysis uses daily confirmed case data collected between September 18, 2020, and April 17, 2022, a period marked by multiple infection waves and heightened transmission risk. COVID-19 trends were categorized into discrete states—decrease, no change, and increase—and modeled to construct transition probability matrices and stationary distributions. These long-term probabilities were then used to generate a regional risk map and inform actuarial pricing of insurance products. The results reveal spatial heterogeneity in case increase probabilities, with Coblong, Arcamanik, and Antapani exhibiting the highest long-term risk. A strong correlation ($R^2 = 0.9473$) was found between case increase probabilities and projected insurance benefits and premiums. The practical implication of this study lies in its provision of a data-driven framework that enables insurance companies to align policy pricing with region-specific and evolving pandemic risks, including long-term health consequences such as post-COVID-19 conditions. This approach enhances both the fairness of premium structures and the financial resilience of insurers in managing future public health crises.

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1. INTRODUCTION

The COVID-19 pandemic, initially identified in December 2019 in Wuhan, China, has since led to a global health crisis and rapidly evolved into a worldwide emergency [1]–[9]. As of January 2023, there have been over 670 million confirmed cases and nearly 7 million deaths globally [10]. In Indonesia, more than 6.8 million infections and 161,900 deaths were recorded as of August 2023 [11]. The pandemic has significantly impacted healthcare systems, disrupted daily life, and caused widespread economic instability, including job losses and financial uncertainty [4] – [6], [8], [12] – [14].

Given the unpredictable nature of the COVID-19 virus and its long-term implications, adopting data-driven strategies is essential to mitigate its effects. These strategies enable policymakers and researchers to develop more effective interventions, minimizing disruptions to public health and economic stability. One such approach is the application of stochastic models, Markov Chains, to forecast future pandemic trends based on observed data. Markov Chain is a stochastic process in which the system moves between states according to probabilities [15] – [19]. The strength and effectiveness of Markov Chains in modeling complex systems have been well established over the years. This model is a powerful tool for predicting the progression of stochastic processes, where future states depend on the present state rather than on past events [19] – [22], [22] – [28]. By capturing the inherent uncertainty and randomness of the pandemic's progression, Markov Chains allow for the estimation of transition probabilities between various states.

Insurance companies were affected by the pandemic, as increased health risks heightened the financial burden on policyholders and insurers [29] – [35]. To ensure financial sustainability and equitable coverage, life insurance premiums and benefits must adapt to evolving epidemiological risks. This study employs a Markov Chain model to analyze daily COVID-19 case data and estimate long-term transmission probabilities across Bandung's sub-districts. These probabilities inform a regional risk map that enables insurers to calibrate premiums and benefits based on localized risk levels, aligning pricing with actual exposure. While lower-risk zones could support cheaper pricing, high-risk areas would require greater payments. Beyond acute infection trends, insurers must also consider the actuarial implications of post-COVID-19 conditions—such as persistent respiratory, cardiovascular, and neurological complications—which can elevate long-term morbidity, mortality, and claims. By integrating forecasted case trajectories with the emerging burden of post-acute effect, this model offers a robust framework for dynamic and risk-adjusted insurance valuation. It supports more responsive pricing strategies that reflect both immediate transmission risk and the protracted health impacts of the pandemic.

Although Markov Chain models have been extensively applied in modeling the progression of infectious diseases, including COVID-19, most existing studies have centered around simulating epidemic dynamics or evaluating transmission patterns over time. For instance, prior research has developed both continuous and discrete stochastic Markov models to simulate epidemic dynamics and forecast outbreaks, analyze clinical risk factors, and capture spatio-temporal patterns in transmission. These include works by [20], [23], [25], [28]. In addition, other studies have investigated national trend predictions [36], long-term epidemic behaviors such as extinction and stationarity [37], and general insurance applications [24]. While these contributions have significantly advanced understanding of the epidemiological dynamics of COVID-19, they tend to focus either on the statistical modeling of the disease or on general spatial-temporal visualization without integrating those insights into a practical financial or actuarial framework.

In this study, we adopt discrete-time Markov Chain as the primary modeling framework for estimating day-to-day progression of COVID-19 cases in Bandung. Markov Chains provide a probabilistic structure that captures stochastic transitions between states over time, making them well-suited for modeling the evolution of infectious disease outbreaks [38]. This modeling approach has previously been applied across various epidemiological contexts, including in the spread of the citrus tristeza virus [39], the H1N1 influenza pandemic [40], and Ebola outbreaks [41]. In the context of COVID-19, it has been used to simulate epidemic progression, forecast trends, analyze spatial dependencies, and explore hidden spatio-temporal structures. However, these studies have largely remained within the boundaries of epidemiological modeling, without extending their results to inform region-specific actuarial decision-making. In contrast, this study applies a discrete-time Markov Chain to categorize daily new COVID-19 cases into states to construct transition probabilities and derive long-term stationary distributions. These serve as the basis for estimating regionally adjusted life insurance benefits and premiums, grounded in a probabilistic understanding of the local transmission risk.

Despite the methodological diversity in prior studies, there remains a notable gap in linking Markov Chain-based disease modeling with financial risk frameworks in a spatially disaggregated context. The integration of epidemic trends into actuarial pricing at the sub-district level has not been sufficiently explored. Existing approaches to insurance modeling rarely incorporate epidemiological dynamics or adapt premiums based on localized transmission risks. To address this gap, this research develops a novel framework that combines stochastic modeling of COVID-19 case progression with spatially sensitive life insurance valuation. By applying this approach to 30 sub-districts in Bandung, we generate a data-driven risk map and quantify region-specific life insurance premiums and benefits. This contributes to the literature by bridging epidemiological modeling with actuarial science, offering a dynamic, equitable, and regionally responsive method for managing financial protection in the context of public health crises.

The primary objective of this research is to integrate long-term COVID-19 case probabilities into life insurance assessments, providing an innovative framework for risk-based pricing. By combining Markov Chain modeling with regional risk mapping, this study offers a novel perspective on pandemic risk management in the insurance industry. The findings contribute to the broader literature on actuarial science and provide actionable insights for insurers seeking to navigate the uncertainties of global health crises. Ultimately, this research highlights the importance of dynamic, data-driven models in managing the economic and health-related risks posed by COVID-19.

2. RESEARCH METHODS

This research employs a stochastic modeling approach using Markov Chain to estimate long-term COVID-19 case trends and its implications for life insurance premiums and benefits in Bandung. Methodology consists of several key stages, including the formulation of the Markov Chain model, estimation of transition probabilities, stationary distribution analysis, calculation of life insurance benefits and premiums, risk mapping, discussion and model limitations.

The data used in this study comprises confirmed COVID-19 cases from September 18, 2020, to April 17, 2022, in Bandung, Indonesia. The dataset contains information on active cases, deaths, and recoveries, with 577 data points recorded for each date across 30 sub-districts in Bandung. The data were obtained from the official Bandung COVID-19 information portal https://covid19.bandung.go.id/.

2.1 Markov Chain Model for COVID-19 Case Trends

Markov Chain is a stochastic process that represents a sequence of probable events in which the probability of transitioning to a future state depends only on the present state and not on the sequence of preceding events [15]. This property, known as the memoryless property, makes Markov Chains highly suitable for modeling dynamic systems such as the spread of infectious diseases **[17]**. A stochastic process is considered to be a Markov chain if for all circumstances $i_0, i_1, \dots, i_{t-2}, i, j$ meet the following equation

$$P(X_t = j \mid X_{t-1} = i, X_1 = i_1, X_0 = i_0) = P(X_t = j \mid X_{t-1} = i) = P_{ij} \tag{1}$$

where P_{ij} denotes the probability that the transition from a process in state i at time t and will be in event j at time $t+1$. Hence, the occurrence of X_t depends only on the occurrence X_{t-1} and is independent of the preceding events $X_0, X_1, \dots, X_{t-1}$.

The implementation of the Markov Chain model in this study involves several structured stages. First, the state space was defined by categorizing daily COVID-19 case trends into three states: decrease (-1), no change (0), and increase (1). Next, transition frequencies between these states were calculated from historical data to construct a 3×3 transition probability matrix for each sub-district. The model was then evaluated to ensure it satisfied key Markov properties—irreducibility, aperiodicity, and positive recurrence—which confirm the existence of a unique stationary distribution. This stationary distribution represents long-term state probabilities, was computed and interpreted as the likelihood of persistent case trends within each region. These probabilities serve as critical inputs for subsequent actuarial modeling of life insurance premiums and benefits, allowing the integration of long-term epidemiological risk into financial forecasting.

2.2 Transition Probability

Transition probability in this study refers to the probability of shifting from one COVID-19 case trend state to another in the Markov Chain model. The states in this Markov model are defined as Table 1:

Table 1. State Space Definition

State	Description
-1	Represents a decrease in COVID-19 cases compared to the previous day
0	Represents no change in COVID-19 cases compared to the previous day
1	Represents an increase in COVID-19 cases compared to the previous day

The possible states include an increase from the previous day (denoted as 1), no change from the previous day (denoted as 0), and a decrease from the previous day (denoted as -1). If the number of cases decreased, the day was classified as State (-1), and so on. Transition probability quantifies the probability of moving from one of these states to another in the next time step, based only on the present state, following the Markov property (memoryless process).

Transition between these states occurs probabilistically, based on observed historical data of COVID-19 case trends. Transition probability matrix is derived using the Chapman-Kolmogorov equation, allowing the model to estimate long-term trends in the spread of COVID-19. Chapman-Kolmogorov equation is used to model the transition probabilities between states over time. This equation provides the mathematical foundation to calculate the probability of being in a particular state after n steps, considering the initial state. The general form of the Chapman-Kolmogorov equation consists of the following formula [15]:

$$P^{(n)} = \boldsymbol{P} \,.\, P^{(n-1)} \tag{2}$$

where $P^{(n)}$ represents the state probability after n transitions, and $\boldsymbol{P}$ is the transition probability matrix. Consider $\boldsymbol{P}$ as a one-step transition probability matrix for the transition probabilities P_{ij}, where $i, j = 0,1,2, \ldots$ The transition probability matrix is defined as follows [15]:

$$\boldsymbol{P} = \begin{bmatrix} \boldsymbol{p_{00}} & \boldsymbol{p_{01}} & \boldsymbol{p_{02}} & \cdots \\ \boldsymbol{p_{10}} & \boldsymbol{p_{11}} & \boldsymbol{p_{12}} & \cdots \\ \boldsymbol{p_{20}} & \boldsymbol{p_{20}} & \boldsymbol{p_{20}} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix} \tag{3}$$

2.3 Stationary Distribution of the Markov Chain

The model assumes that the Markov Chain will reach a stationary distribution over time, where the state probabilities no longer change with additional transitions. The stationary distribution is essential for estimating the long-term probabilities of COVID-19 case trends, which directly inform the life insurance calculations. The Markov Chain is considered stationary if it is aperiodic, positive recurrent, and irreducible, as these properties guarantee convergence to a unique stationary distribution. Irreducibility ensures that all states are accessible from any other state, meaning that no sub-district is permanently stuck in one trend. Aperiodicity guarantees that system does not follow a strict cycle. It allows probabilities to settle into a stable distribution. Positive recurrence ensures that every state is revisited within a finite period. Thus, the system does not diverge indefinitely. Mathematically, stationary distribution is defined as a probability vector:

$$\boldsymbol{\pi P} = \boldsymbol{P} \tag{4}$$

where $\boldsymbol{P}$ is the transition probability matrix, and $\boldsymbol{\pi}$ is the stationary probability vector that represents the long-term probabilities of being in each state. The stationary probabilities are obtained by solving this equation under the condition that the sum of all probabilities equals 1:

$$\boldsymbol{\Sigma \pi_i = 1} \tag{5}$$

Stationary distribution results provide a critical foundation for analyzing the long-term impact of COVID-19 trends in Bandung City. These probabilities are later used for risk assessment.

2.4 Life Insurance Benefits Estimation

To estimate life insurance premiums and benefits, two main components are considered. Benefits are calculated using the following formula:

$$\bar{A}^{ij}_{s:\bar{n}|} = \int_0^n b_t v^t {}_t p_s^{ij}\, \mu_s^{ij}\, dt \tag{6}$$

where i represents initial state of the policyholder, j is the final state of the policyholder, $\bar{A}^{ij}_{s:\bar{n}|}$ define the expected benefits value paid upon the transition from state i to state j at location s over n years, b_t shows benefit at time t, v^t represents discounted factors, ${}_t p_s^{ij}$ define probability of an individual transitioning from state i to state j at location s, and the μ_s^{ij} is a transition rate.

2.5 Life Insurance Premiums Estimation

The estimation of life insurance premiums in this study is based on the expected life insurance benefits and the long-term probability distribution of COVID-19 case trends. Since life insurance premiums must accurately reflect the risks associated with different regions, the Markov Chain stationary distribution is used to assess the probability of case fluctuations over time. Areas with higher probabilities of sustained case increases are assigned higher premiums, while lower-risk areas receive lower premium rates.

To calculate life insurance premiums, this study applies actuarial pricing models that consider the relationship between expected benefit amounts, transition probabilities, and annuity factors. The premium estimation follows the formula:

$$\pi_{s:\bar{n}|}{}^{i,j} = \frac{\bar{A}\,_s^{i,j}}{\bar{a}\,_s^{i,j}} \tag{7}$$

$$\pi_{s:\bar{n}|}{}^{i,j} = \frac{\int_0^n b_t v^t {}_t p_s^{ij}\, \mu_s^{ij}\, dt}{\int_0^n b_t v^t {}_t p_s^{ij}\, dt} \tag{8}$$

where the following notations apply: $\pi_{s:\bar{n}|}{}^{i,j}$ represents expected premium value paid by the policyholder when transitioning from state i to state j at location s over a period of n years, $\bar{A}\,_s^{i,j}$ means expected benefits value paid upon the transition from state i to state j at location s over n years, and $\bar{a}\,_s^{i,j}$ is annuity from state i to state j at location s.

2.6 Limitations of the Model

This study's Markov Chain model provides a structured approach to estimating COVID-19 risk trends and their impact on life insurance. However, limitations exist that must be considered. One key limitation is the model assumes static mortality rates and discount factors, even though these variables fluctuate due to medical advancements and economic changes. The stationary distribution assumption also simplifies reality, as pandemics are unpredictable and influenced by sudden epidemiological shifts. Data limitations present another challenge. The available COVID-19 case data is incomplete, potentially leading to inaccuracies in transition probability estimation. A more comprehensive dataset could improve prediction accuracy and provide a stronger foundation for insurance calculations. Moreover, the model does not account for spatial dependencies between sub-districts, meaning interactions between neighboring regions are not considered.

Despite these limitations, the model remains a valuable tool for actuarial risk assessment. For future improvements, such as incorporating dynamic transition probabilities, economic variables, and complete datasets, could enhance its predictive power and real-world applicability.

3. RESULTS AND DISCUSSION

3.1 Descriptive Statistics

The data used in this study comprises confirmed COVID-19 cases from September 18, 2020, to April 17, 2022, in Bandung, Indonesia. The dataset contains information on active cases, deaths, and recoveries. Observations were recorded for 577 data points per date across 30 sub-districts in Bandung. Daily confirmed COVID-19 cases across 30 sub-districts in Bandung City are presented in Fig. 1 as follows.

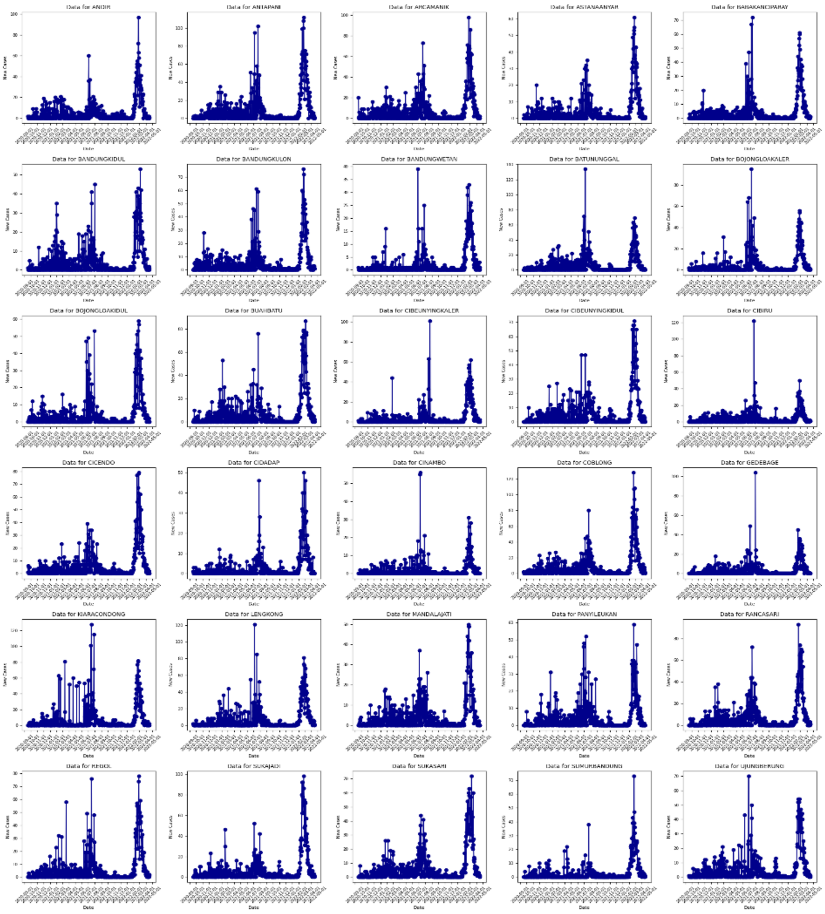


Figure 1. Daily Confirmed COVID-19 Cases in 30 Sub-Districts of Bandung

The graphs shown in Fig. 1 presents the descriptive statistics for the daily confirmed COVID-19 cases across the 30 sub-districts of Bandung from September 18, 2020, to April 17, 2022. The mean number of daily cases varied considerably across sub-districts, ranging from 1.702 in Cinambo to 8.109 in Antapani, indicating a heterogeneous distribution of the disease burden throughout the city. The standard deviations were generally high, with a maximum standard deviation of 16.68 observed in Antapani and a minimum of 4.88 in Cinambo, suggesting substantial day-to-day fluctuations in case counts within each sub-district. Skewness values were positive for all sub-districts, ranging from 2.88 to 7, implying a rightward skew in the distribution of daily cases, with occasional surges leading to a long tail. Kurtosis values were also high, ranging from 8.84 to 82.27, showing leptokurtic distributions. Leptokurtic distributions show sharper peaks and heavier tails than normal distributions. These high kurtosis values suggest the presence of outlier events (e.g., superspreading events) that disproportionately contributed to the overall case counts. The daily case counts across 30 sub-districts, illustrated in Fig. 1, reflected the wave-like pattern of the pandemic during the study period. The higher mean cases and standard deviations observed in Antapani, Coblong, and Arcamanik, may attributable to higher population densities, increased mobility, or differences in adherence to public health measures.

3.2 Transition Probability

Following the determination of state frequencies and the classification of daily COVID-19 case trends into the defined states (decrease, no change, increase), the next step involved calculating the transition probabilities between states. Transition probabilities quantify the probability of moving from one state to another between consecutive days, providing insights into COVID-19 transmission. This study's transition probability $\boldsymbol{p_{ij}}$ represents probability of transitioning from state $\boldsymbol{i}$ to state $\boldsymbol{j}$. Key findings from the transition probability analysis reveal a diverse range of transition patterns across 30 sub-districts. A summary of transition patterns across sub-districts can be seen from the transition probability matrix. This underscore spatially heterogeneous transmission across sub-district in Bandung.

To illustrate the process of state classification and transition, this figure presents a snapshot of confirmed COVID-19 cases and state transitions over six consecutive days in three representative sub-districts (Andir, Antapani, Arcamanik). Each sub-district's state was derived by comparing the cumulative number of confirmed cases with those of the preceding day.

Table 2. Daily State Transitions of COVID-19 Cases

Date	Andir	Andir_State	Antapani	Antapani_State	Arcamanik	Arcamanik_State
18/09/2020	57	1	49	0	53	1
19/09/2020	58	1	51	1	53	0
20/09/2020	58	0	53	1	54	1
21/09/2020	58	0	53	0	60	1
22/09/2020	58	0	53	0	60	0
23/09/2020	58	0	53	0	60	0

After classifying daily COVID-19 case trends into discrete states, the subsequent step involves calculating the frequency of each state across the observed period. This step provides the empirical basis for estimating transition probabilities. As shown, each sub-district (Andir, Antapani, and Arcamanik) exhibits a distribution of state occurrences with comparable totals (576 observations per district), reflecting a balanced representation of each state. These frequencies are then used to construct the one-step transition probability matrix, where each entry p_{ij} represents the likelihood of transitioning from state i to state j, forming the foundation for further analysis of long-term COVID-19 trends through stationary distribution modeling.

Table 3. Cumulative State Transitions of COVID-19 Cases

State Description	Andir	Antapani	Arcamanik
Frequency of State "-1"	208	207	206
Frequency of State "0"	161	149	147
Frequency of State "1"	207	220	223
Total	**576**	**576**	**576**

Based on Cumulative State Frequencies on Table 3, the empirical one-step transition probability matrix was constructed for 30 sub-district by dividing the number of transitions from a given state i to another state j by total occurrences of state i. This matrix captures the probability of changes in COVID-19 case trends between consecutive days and provides insights into the stochastic behavior of case dynamics. The transition probability matrices for Andir, Antapani, and Arcamanik are presented below.

Table 4. Transitions Probability Matrices of COVID-19 Cases

Andir				Antapani				Arcamanik			
From/To	-1	0	1	From/To	-1	0	1	From/To	-1	0	1
-1	$\frac{51}{208}$	$\frac{55}{208}$	$\frac{102}{208}$	-1	$\frac{42}{207}$	$\frac{54}{207}$	$\frac{111}{207}$	-1	$\frac{42}{206}$	$\frac{37}{206}$	$\frac{127}{206}$
0	$\frac{19}{161}$	$\frac{86}{161}$	$\frac{56}{161}$	0	$\frac{16}{149}$	$\frac{80}{149}$	$\frac{53}{149}$	0	$\frac{8}{147}$	$\frac{99}{147}$	$\frac{40}{147}$
1	$\frac{137}{207}$	$\frac{21}{207}$	$\frac{49}{207}$	1	$\frac{149}{220}$	$\frac{16}{220}$	$\frac{55}{220}$	1	$\frac{155}{223}$	$\frac{12}{223}$	$\frac{56}{223}$

To provide a clearer view of how the transition probabilities were empirically derived, each element in the transition matrix is expressed in its fractional form. The numerators represent the observed number of transitions from state i to state j, while the denominators indicate the total frequency of the originating state i in each sub-district.

$$
{}_t\boldsymbol{P}^{i,j}_{(\boldsymbol{Andir})} = \begin{pmatrix} \frac{51}{208} & \frac{55}{208} & \frac{102}{208} \\ \frac{19}{161} & \frac{86}{161} & \frac{56}{161} \\ \frac{137}{207} & \frac{21}{207} & \frac{49}{207} \end{pmatrix} \quad {}_t\boldsymbol{P}^{i,j}_{(\boldsymbol{Antapani})} = \begin{pmatrix} \frac{42}{207} & \frac{54}{207} & \frac{111}{207} \\ \frac{16}{149} & \frac{80}{149} & \frac{53}{149} \\ \frac{149}{182} & \frac{16}{182} & \frac{55}{182} \end{pmatrix} \quad {}_t\boldsymbol{P}^{i,j}_{(\boldsymbol{Arcamanik})} = \begin{pmatrix} \frac{42}{206} & \frac{37}{206} & \frac{127}{206} \\ \frac{8}{147} & \frac{99}{147} & \frac{40}{147} \\ \frac{140}{223} & \frac{12}{223} & \frac{56}{223} \end{pmatrix}
$$

3.3 Stationary Distribution Markov Chain for COVID-19

Stationary probabilities denoted by π, represent long-term distribution of states under Markov Chain model for each sub-district. These probabilities indicate steady-state probability of a sub-district experiencing a decrease, no change, or an increase, in COVID-19 cases after many time steps. As shown in Table 5 below, each sub-district converges to a distinct long-term distribution. These stationary probabilities π_{-1}, π_0, π_1 are critical for the subsequent calculation of insurance premiums and benefits. It reflects underlying long-term epidemic risk in each area and serve as a probabilistic baseline for risk-based decision-making.

Table 5. Stationary Probability of COVID-19 Cases

State	Andir	Antapani	Arcamanik	⋯
$\boldsymbol{\pi_{-1}}$ **(Decrease)**	35.90%	35.80%	35.50%	⋯
$\boldsymbol{\pi_0}$ **(No change)**	28.20%	26.20%	25.90%	⋯
$\boldsymbol{\pi_1}$ **(Increase)**	35.90%	38.00%	38.60%	⋯

Each transition matrix contains a single communication class, indicating that the Markov chains are irreducible. Furthermore, all states were found to be aperiodic and recurrent, and positive recurrence was confirmed through n-step transition matrix evaluations as n approaches infinity. Consequently, each Markov chain admits a unique stationary distribution.

Given the focus on high-risk scenarios, this study prioritizes the transition rate associated with state in Eq. (1), representing an increase in COVID-19 cases from the previous day. Transition rate, denoted as $\boldsymbol{\mu^{i,j}}$, quantifies the frequency of movement into this state. These calculated transition rates, presented in Table 6 as the foundation for the subsequent stationary distribution analysis, which further examines the long-term probabilities of COVID-19 case trends. The results of this analysis will then be integrated into the estimation of insurance premiums and benefits.

Table 6. Transition Rates of States $(\mu^{i,j})$

Sub-District	$(\boldsymbol{\mu^{-1,1}})$	$(\boldsymbol{\mu^{0,1}})$	$(\boldsymbol{\mu^{1,1}})$
Andir	0.184	0.104	0.082
Antapani	0.178	0.096	0.085
Arcamanik	0.219	0.066	0.093
⋮	⋮	⋮	⋮

After determining transition probabilities, the next step is to compute the stationary distribution. Understanding stationary distribution of COVID-19 case trends is essential for predicting the pandemic's long-term behavior and its implications for public health planning. Policymakers can design targeted interventions in high-risk areas by analyzing how case states (decrease. stability. or increase) stabilize over time. In this research, stationary distribution represents long-term behaviour of COVID-19 case trends across 30 sub-districts in Bandung. Stationary distribution occurs when the probabilities of being in each state stabilize over time, meaning they no longer fluctuate with additional transitions. Markov Chain satisfies the key properties necessary for the existence of a stationary distribution:

1. Irreducibility ensures that all states remain accessible over time, meaning no sub-district is permanently locked in a single trend.
2. Aperiodicity: System must not be cyclic. It allows to settle into a stable probability distribution over time. Since the transitions between states are observed daily, no fixed periodic cycle in Markov Chain satisfies this condition.
3. Positive Recurrence: Each state must eventually be revisited in a finite time. ensuring the system does not diverge. The transition probability matrix was evaluated as $n \to \infty$ that demonstrate every state is positively recurrent. Thus. it confirms that the Markov Chain converges to a stationary distribution.

These properties confirm that the probabilities will converge to a stable long-term distribution and allow for a robust assessment of sub-district-level COVID-19 risk. High probability of sustained case increases in Coblong (39.91%), Arcamanik (38.87%), and Antapani (37.62%) may be attributed to several factors. These sub-districts have higher population densities, leading to increased human interactions and greater transmission risk. Additionally. they are commercial hubs where significant daily movement contributes to higher exposure rates. Conversely, Bandung Kulon (15.14%), Cibiru (15.62%), and Bandung Wetan (22.30%) have lower probabilities of sustained case increases. These areas are characterized by lower population densities and less urban mobility.

The chart shown in Fig. 2 is a heatmap visualization created to help with a more precise assessment of these long-term probabilities. This heatmap categorizes sub-districts based on their stationary probabilities.

providing a spatial representation of areas where COVID-19 cases are most likely to remain high over time. The following section expands this visualization through a risk map. The probabilities are listed sequentially as $\boldsymbol{\pi_1}.\boldsymbol{\pi_0}.\boldsymbol{\pi_{-1}}$.

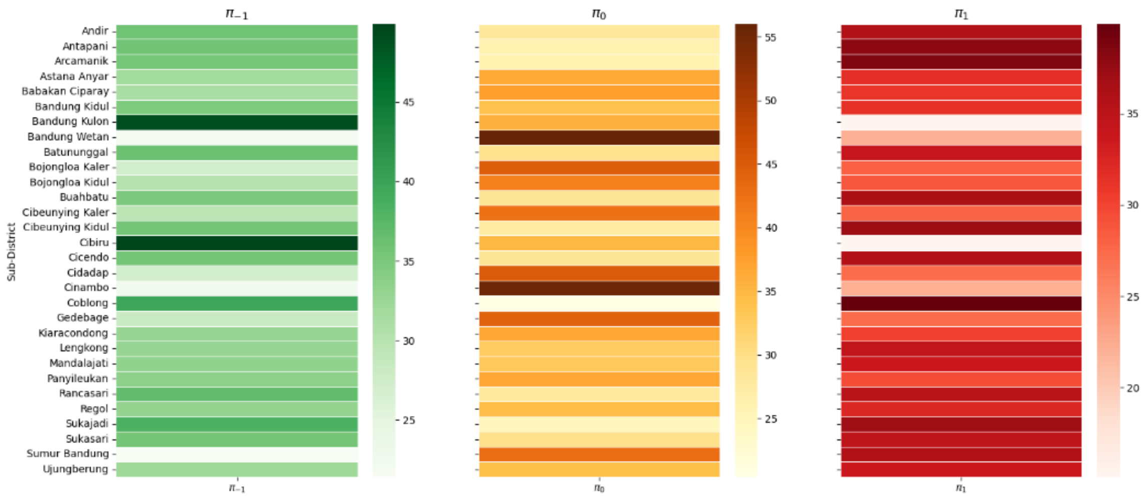


Figure 2. Heatmap of Stationary Distribution Across 30 Sub-Districts of Bandung City

The chart shown in Fig. 2 presents the highest probability trends in each sub-district. It classify regions based on their probability of remaining in an increasing, stable, or decreasing state. Three of these trends include an increase, stability, or decrease in COVID-19 cases compared to the previous day. For instance, sub-districts of Bandung Wetan and Bandung Kidul both display a yellow color. However, the intensity of the yellow color differs between the two sub-districts. In Bandung Wetan, the yellow is more intense due to a higher probability of stability in COVID-19 cases compared to the previous day, in contrast to Bandung Kidul. These long-term probabilities serve as input for the subsequent insurance premium and benefit estimation analysis. By incorporating stationary distributions, insurers can better anticipate future claim rates and set appropriate pricing structures to ensure financial sustainability.

3.4 Risk Map of COVID-19 in Bandung

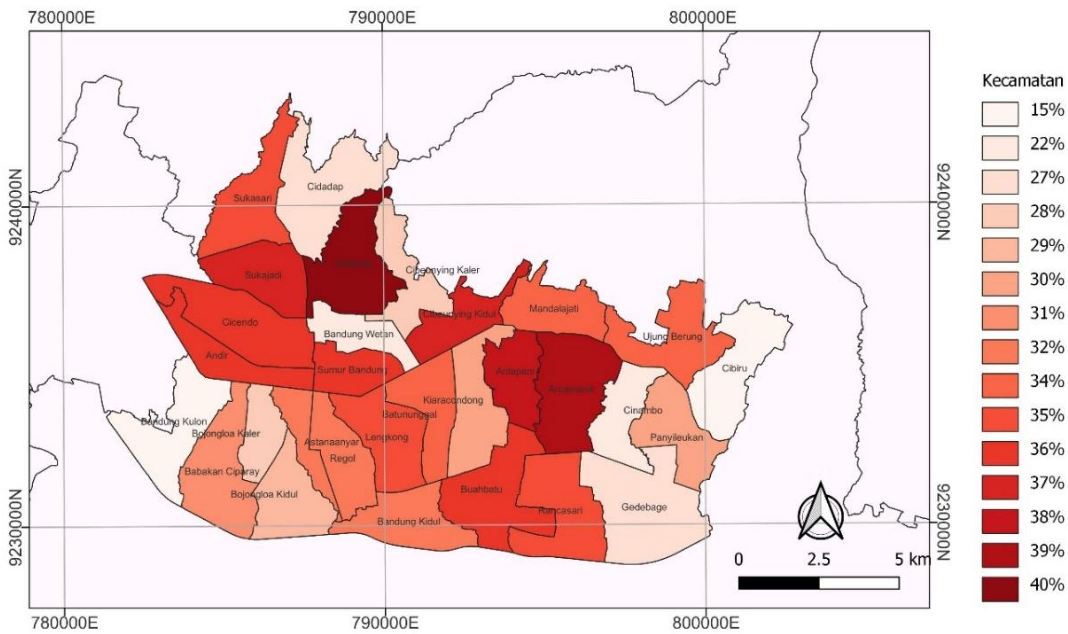


Figure 3. Risk Map: Distribution of COVID-19 Case Increase Probabilities in Bandung

The risk map in Fig. 3 serves as a tool for translating numerical stationary probabilities into insights for public health and insurance risk assessment. By categorizing sub-districts based on their probability of sustained case increases, a risk map helps identify COVID-19 hotspots. Color gradient in risk map directly reflects probability of case increases. Darker red shades indicate a higher probability of sustained COVID-19 transmission, while lighter shades correspond to areas with lower long-term risk. For example, Coblong (40%), Arcamanik (39%), and Antapani (38%), exhibit intense red shading, aligning with their high stationary probabilities of case increases. In contrast, Bandung Kulon (15%), Cibiru (15%), and Bandung Wetan (22%) appear in lighter hues, consistent with their lower probability values. This visualization reinforces the spatial heterogeneity of COVID-19 transmission risk across Bandung.

Risk map has implications for both public health policy and insurance risk assessment. For policymakers. the identification of high-risk areas enables the prioritization of testing efforts. vaccination campaigns. and healthcare resource allocation. While for insurance providers. the risk classification can inform data-driven adjustments to premium pricing and benefit structures based on localized COVID-19 risks. Through the combination of spatial visualization and stationary distribution analysis. the risk map offers a thorough framework for evaluating the long-term effects of COVID-19 on various sub-districts. The next chapter extends this analysis into the financial domain. which examines how these long-term probabilities influence life insurance premiums and benefits estimation.

3.5 Life Insurance Benefit Estimation

This study uses Markov model to estimate life insurance payouts based on the long-term probability of COVID-19 trends. Insurers provide these advantages as compensation to reduce the financial risks related to COVID-19's consequences. Discount factors. transition rates. and stationary distribution probabilities are used to calculate the estimated payoff for different risk levels over 30 sub-districts in Bandung.

Table 7. Projected Life Insurance Benefit (in million IDR)

Sub-District	-1.1	0.1	1.1
Andir	2.34	0.94	0.50
Antapani	2.47	0.89	0.55
Arcamanik	3.50	0.47	0.60
Astana Anyar	2.06	0.80	0.19
Babakan Ciparay	1.71	0.71	0.29
Bandung Kidul	2.38	0.55	0.28
Bandung Kulon	2.16	0.90	0.57
Bandung Wetan	0.50	0.57	0.15
Batununggal	2.28	0.69	0.47
Bojongloa Kaler	0.93	0.77	0.22
Bojongloa Kidul	1.06	0.65	0.21
Buahbatu	2.51	0.52	0.73
Cibeunying Kaler	1.37	0.64	0.19
Cibeunying Kidul	2.51	0.69	0.73
Cibiru	2.25	0.95	0.42
Cicendo	2.29	0.77	0.56
Cidadap	1.15	0.82	0.15
Cinambo	0.69	0.64	0.08
Coblong	2.79	1.02	0.78
Gedebage	1.35	0.54	0.38
Kiaracondong	1.54	0.68	0.30
Lengkong	2.46	0.73	0.39
Mandalajati	1.92	0.93	0.49
Panyileukan	2.23	0.42	0.20
Rancasari	2.33	0.60	0.59
Regol	1.97	0.41	0.52
Sukajadi	2.61	0.84	0.39
Sukasari	2.60	0.76	0.38
Sumur Bandung	0.49	0.73	0.08
Ujungberung	1.78	0.98	0.48

Results show that sub-districts with higher probabilities of transitioning to a state of increasing cases. such as Coblong (39.91%). Arcamanik (38.87%), and Antapani (37.62%), receive the highest estimated benefits: Rp 2.79 million, Rp 3.50 million, and Rp 2.47 million, respectively. In contrast. sub-districts with lower probabilities of case increases including Cinambo (15.14%), Sumur Bandung (15.62%), and

Bandung Wetan (22.30%), have lower estimated benefit values with payouts of Rp 0.69 million, Rp 0.49 million, and Rp 0.5 million, respectively.

The value of life insurance benefits (in IDR) represents the financial amount required to be provided by the government or insurance firms in the event of an adverse risk occurrence. The estimated payouts are calculated based on state transitions, where COVID-19 case numbers are expected to increase. Given the significant risk involved, the study focuses on state transitions that result in an escalation of daily cases, specifically $(-1,1), (0,1)$, and $(1,1)$. These transitions reflect scenarios where case counts shift from a decrease to an increase $(-1,1)$, from stability to an increase $(0,1)$, and from an increase to a sustained increase $(1,1)$. The estimated life insurance benefits for each transition provide insight into financial compensation required for these risk scenarios. The $(-1,1)$ transition represents expected benefit to be disbursed when daily cases shift from a decrease to an increase, indicating a sudden resurgence of infections. The $(0,1)$ transition signifies the anticipated benefit for a shift from stable case numbers to an increase. It highlights transmission risks. Lastly, the $(1,1)$ transition reflects estimated benefit value for the persistence of case increases and represents prolonged pandemic conditions. Fig. 4 illustrates the relationship between probability of case increases and corresponding life insurance benefits, demonstrating how higher pandemic risks correlate with more financial compensation requirements.

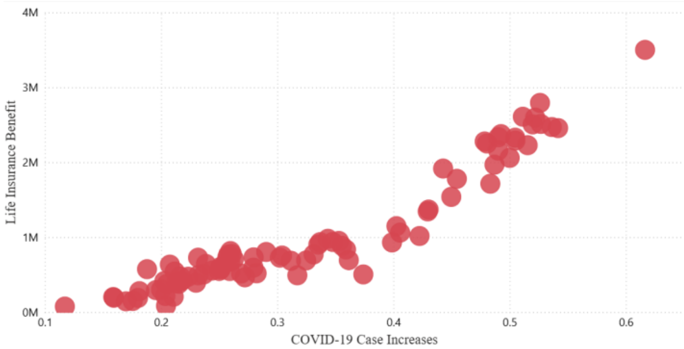
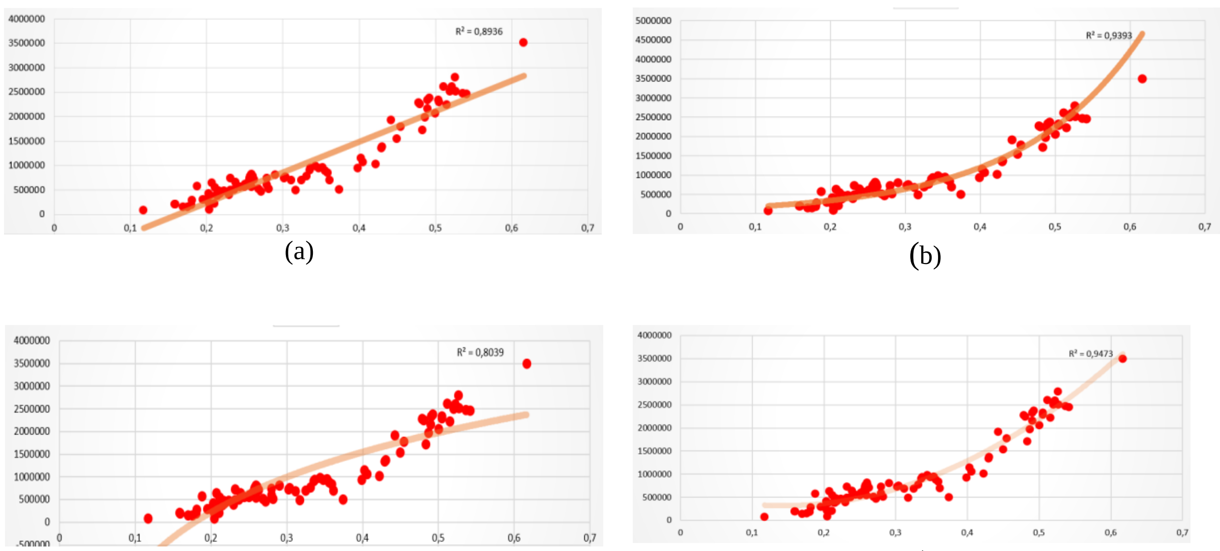


Figure 4. COVID-19 Case Increases vs. Life Insurance Benefits

It is evident that as the probability of a rise in COVID-19 cases increases, so does the amount of benefits that the government and insurance companies are required to provide. To determine the nature of this relationship, the selection of the most appropriate trend model can be made by comparing coefficient of determination (R^2) values and values and examining the model curve that best aligns with historical data. The coefficient of determination is a statistical measure that evaluates the proportion of variance in dependent variable that evaluates the proportion of variance in dependent variable and can be explained by independent variable in a regression model. In this context, R^2 quantifies the goodness of fit of the regression model to historical data. It is indicate how well the model represents the observed relationship between COVID-19 case probabilities and insurance benefit estimations. It is calculated by comparing the sum of squared differences between the predicted values ($\widehat{Y_t}$) and mean of the observed values ($\bar{Y}$) to total sum of squared differences between the observed values (Y_t) and its mean. A higher R^2 value indicates a better fit of the model to data and suggest that independent variables account for a greater proportion of variability in dependent variable. Coefficient of determination is mathematically expressed as follows:

$$R^2 = \frac{(\sum \widehat{Y}_t - \bar{Y})}{(\sum Y_t - \bar{Y})} \tag{9}$$

Below are several trend model options along with their respective coefficients of determination. illustrated in Fig. 5.



(a) (b) (c) (d)

Figure 5. COVID-19 Case Increases vs. Life Insurance Benefits Trend model options
(a) Linear Trend, (b) Exponential Trend, (c) Logarithmic Trend, (d) Second Order Polynomial.

The trend model options illustrating the relationship between the probability of a rise in COVID-19 cases and life insurance benefits is presented in Fig. 5. Among the models, the second-order polynomial trend demonstrates the best coefficient of determination ($R^2 = 0.9473$) that indicates the strongest fit to data. The R^2 values for the remaining models are as follows: Linear ($R^2 = 0.8936$). Exponential ($R^2 = 0.9393$). and Logarithmic ($R^2 = 0.8039$). These results suggest that the relationship between the probability of an increase in COVID-19 cases and life insurance benefits is best represented by a second-order polynomial trend, which captures the nonlinear nature of the data more accurately than other models. A polynomial trend is beneficial for identifying patterns in datasets with curvature, which is often observed in large datasets with significant variability. The polynomial model is a better option as additional data becomes available since the connection between variables no longer follows a linear pattern.

3.6 Life Insurance Premium Estimation

Life insurance premiums estimation in this study is based on the long-term probabilities of COVID-19 case trends, as derived from the Markov Chain model. Premiums are determined using the annuity factor over a given period and the estimated benefit amounts. The calculation incorporates transition probabilities between states, discount factors, and expected payout values to ensure that premiums accurately reflect regional risk variations. Life insurance premium estimation for each sub-district was computed using equation (8). Life insurance premium estimation for each transition are summarized in Table 8.

Table 8. Projected Life Insurance Premium (million IDR)

Sub-District	**−1. 1**	**0. 1**	**1. 1**
Andir	1.84	1.04	0.82
Antapani	1.78	0.96	0.85
Arcamanik	2.19	0.66	0.93
Astana Anyar	1.59	1.07	0.47
Babakan Ciparay	1.37	1.04	0.58
Bandung Kidul	1.86	0.82	0.60
Bandung Kulon	1.70	1.04	0.88
Bandung Wetan	0.52	1.18	0.33
Batununggal	1.84	0.85	0.82
Bojongloa Kaler	0.90	1.15	0.41
Bojongloa Kidul	1.01	0.99	0.38
Buahbatu	1.93	0.71	1.01
Cibeunying Kaler	1.23	1.04	0.41
Cibeunying Kidul	1.84	0.82	1.10
Cibiru	1.81	1.04	0.74

Sub-District	-1.1	0.1	1.1
Cicendo	1.75	0.90	0.88
Cidadap	1.10	1.21	0.33
Cinambo	0.74	1.18	0.25
Coblong	2.05	0.93	1.15
Gedebage	1.21	0.99	0.68
Kiaracondong	1.32	1.01	0.58
Lengkong	1.75	0.93	0.71
Mandalajati	1.67	1.07	0.82
Panyileukan	1.67	0.79	0.49
Rancasari	1.78	0.82	0.90
Regol	1.56	0.74	0.74
Sukajadi	1.97	0.90	0.66
Sukasari	1.92	0.96	0.71
Sumur Bandung	0.60	1.21	0.16
Ujungberung	1.51	1.10	0.85

The findings show that the largest projected premiums are found in subdistricts with greater probabilities of constant case increases, such as Coblong (2.05 million IDR), Arcamanik (2.19 million IDR), and Antapani (1.78 million IDR). These higher premiums reflect the increased financial risk associated with persistent COVID-19 transmission. In contrast, sub-districts with lower probabilities of case increases, including Cinambo (0.74 million IDR), Sumur Bandung (0.60 million IDR), and Bandung Wetan (0.52 million IDR), have lower estimated premium values, as these areas are characterized by lower transmission risks. The relationship between COVID-19 risk and insurance premiums follows a second-order polynomial trend, with a high coefficient of determination ($R^2 = 0.9473$). Thus, it is confirmed that as the probability of COVID-19 case increases rises, required premium also increase non-linearly.

Structure of life insurance premium is designed to balance financial sustainability and fairness. Several factors influence premium variations across sub-districts. High-risk sub-districts typically have higher population densities, greater mobility, and frequent public interactions, leading to higher premiums. Conversely, lower insurance contributions benefit low-risk areas with less urban activity and lower population densities. Additionally, actuarial adjustments ensure long-term financial stability while offering affordable coverage. The transition probability matrix enables a dynamic pricing structure.

Findings from this study provide insights for insurance companies and policymakers in structuring fair and risk-based premium models. Insurance providers can adjust premiums dynamically based on real-time pandemic risk assessments and ensure that contributions align with regional COVID-19 exposure levels. Higher sub-district premiums with persistent case increases help maintain sufficient insurance reserves to cover potential policyholder claims. Estimating life insurance premiums based on Markov Chain modelling and risk mapping provides a scientific approach to pricing insurance policies during a pandemic.

4. CONCLUSION

This study provides insights into the long-term behavior of COVID-19 transmission across sub-districts in Bandung, revealing significant spatial variation in case trends. The highest probabilities of sustained case increases were observed in Coblong (40%), Arcamanik (39%), and Antapani (38%), while Bandung Kulon (15%), Cibiru (15%), and Bandung Wetan (22%) exhibited the lowest. These findings reflect the geographic heterogeneity of pandemic risk, influenced by factors such as population density, mobility patterns, and urban infrastructure.

By employing a Markov Chain framework, the study effectively modeled daily transitions in COVID-19 case trends—capturing increases, decreases, and stability—and demonstrated that the model satisfies essential stochastic properties, including irreducibility, aperiodicity, and positive recurrence. These properties guarantee convergence to a unique stationary distribution, which accurately represents the long-term probabilities of transmission dynamics.

Crucially, these stationary probabilities were integrated into actuarial pricing models to estimate life insurance benefits and premiums. The analysis revealed a strong nonlinear relationship, modeled using a second-order polynomial with a high coefficient of determination ($R^2 = 0.9473$), between the probability of case increases and corresponding insurance payouts. This confirms that as regional COVID-19 risk rises, so too must insurance contributions and benefits to ensure actuarial fairness and financial sustainability. Overall, the findings highlight the utility of Markov Chain model as data-driven approach for forecasting epidemiological trends and informing dynamic, risk-based insurance strategies in public health crises.

Author Contributions

Hamidah Qurrotun Nadwah: Conceptualization, Data Curation, Formal Analysis, Investigation, Methodology, Project Administration, Resources, Software, Visualization, Writing-original draft, Writing-review and editing. Utriweni Mukhaiyar: Conceptualization, Funding Acquisition, Resources, Supervision, Validation. All authors discussed the results and contributed to the final manuscript.

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Declarations

The authors declare no competing interest.

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