Cancer Insurance Longevity Risk Management – A Natural Hedging Approach

Abstract

This study proposes a natural hedging approach to mitigate the longevity risk of long-term cancer insurance policies. The incidence of cancer is increasing in Taiwan. Conversely, the mortality rates of cancer patients are decreasing with time, making natural hedging a possible solution in dealing with the longevity risk of cancer insurance. We use the claim data from Taiwan's National Health Insurance Database to estimate the trend in cancer incidence rates and post-cancer mortality rates. We demonstrate how the natural hedging strategy can be applied to life insurers' longevity risk management about cancer insurance by arranging the benefits.

Keywords: Cancer Insurance, Longevity Risk, Natural Hedging, Mortality Improvement, National Health Insurance Database

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1. Introduction

The trend of prolonging life expectancy continues, and the need for retired life has become an important issue. Longevity risk refers to the possibility of people outliving their resources, and it is a popular topic in recent years. The risk related to the elderly occurs in three different aspects: financial inadequacy, increasing medical cost, and additional cost of long-term care when older adults live longer than expected. The insurance industry has been searching for solutions to deal with these financial impacts related to longevity risk since the turn of the 21st century. The concept of longevity risk was first proposed for annuity products, but it exists in other insurance products such as long-term care insurance and medical insurance as well (Levantesi and Menzietti, 2012, 2018; Yue et al., 2018).

The longevity risk and its impact are now well recognized by most life insurers. Many solutions were proposed and can be grouped into three types of approaches. The first approach relies on stochastic models; quite a few mortality models were proposed in recent years, including the Lee-Carter (Lee and Carter, 1992), CBD (Cairns et al., 2006), and RH models (Renshaw and Haberman, 2006). These models provide fairly accurate predictions for mortality rates, and further modifications to these mortality models were proposed to improve the fitting or forecasting accuracy (e.g., Li and Lee, 2005; Russolillo et al., 2011; Villegas et al., 2016). However, the model performance is somewhat data-dependent and sensitive to estimation methods.

The second approach is to transform risks through capitalization. For example, with the innovation of mortality-related derivatives, life insurers can transfer the longevity risk to investors in the capital market (Blake and Burrows, 2001; Lin and Cox, 2005, Dowd et al., 2006a, and 2006b; Stevens et al., 2010). Wong et al. (2017a) proposed a solution for life insurers'

hedging strategies when the underlying mortality rates of insurance liabilities are correlated and cointegrated with the index mortality rates. However, the lack of pricing transparency, high transaction costs, and potential default risk limit the development of mortality security-related products.

The third approach is to immunize or eliminate the impact of longevity risk through the characteristics of different products issued by the same life insurer, usually referred to as immunization or natural hedging. Wang et al. (2010) proposed the immunization theory approach, showing that life insurers can eliminate longevity risk by matching policy durations. Noticing that values of life insurance and annuity liabilities move in opposite directions in response to a change in mortality, Cox and Lin (2007) proposed a natural hedging strategy that stabilizes insurers' aggregate liability cash flows. Wong et al. (2017b) used stochastic mortality and interest rate models to assess life insurance and annuity capital requirements and quantify the benefits of natural hedging for different types of life insurance products and portfolios. Life insurers can utilize natural hedging or the immunization strategy without access to the capital market and with limited additional operational costs. Most past studies on longevity risk management focus on life insurance and annuity, but rarely on other types of insurance products, such as health and long-term care insurance. Recently, researchers have begun to specify the longevity risk that underlies these products. Levantesi and Menzietti (2018) applied natural hedging strategies for long-term care insurers by diversifying longevity and disability risk through a product mix including whole life, annuity, and long-term care insurance.

As cancer is the leading cause of death in many Asian countries, cancer insurance has become a popular health insurance product. However, the impact of mortality reduction on cancer incidences and medical costs can be highly debatable. One conjecture is that mortality reduction implies a higher cancer incidence and increases the cost of future medical and supplemental coverages. Conversely, one may argue that mortality reduction can be accompanied by healthier lifestyles, reducing cancer incidence, improved longevity

accompanied with better health care may reduce the post-cancer recovery time and medical costs. From Taiwan's National Health Insurance Dataset (NHID), we found that Taiwanese males' and females' overall cancer incidence rate gradually increases from 1999 to 2016, as shown in Figure 1. Yue et al. (2018) also showed that Taiwanese insurers who issue cancer insurance products are exposed to longevity risk with increasing cancer incidence and decreasing mortality rates, worsening the loss ratio, which can be 150% or more. Based on these observations, we stand by the conjecture that mortality reduction implies a higher cost for cancer insurance and focus our study on the natural hedging of life insurers' cancer insurance longevity risk management.

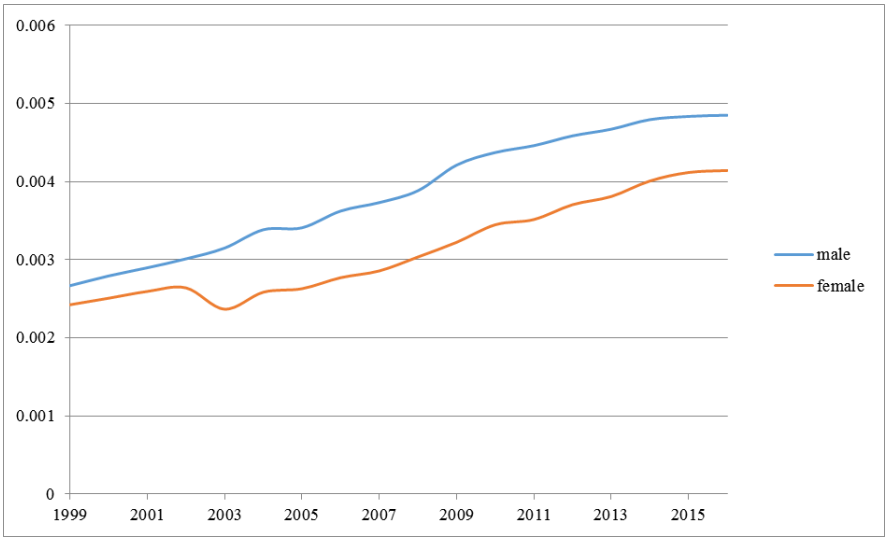

Figure 1. Cancer incidence rates from Taiwan's NHI Database (1999–2016)

Here, we study the impact of mortality improvement on Taiwan's life insurers who issue whole-life[1] cancer insurance policies and propose a natural hedging approach to mitigate the risk. In Taiwan, cancer insurance is the most common form of health insurance. In 2019, every Taiwanese person had three health insurance policies, including one cancer insurance policy (Taiwan Insurance Institute). After the insured is diagnosed with cancer, these policies usually

[1] Although these policies are named "whole-life," they usually terminate when the insured reaches a certain age, e.g., 90 or 95.

provide benefits, including inpatient stays, outpatient visits, surgical costs, and prescription drugs. Post-cancer death benefits are also included if the insured passes away after being diagnosed with cancer. Life insurers face pricing and longevity risks for cancer insurance, and this is the main reason why some life insurers have claimed that the loss ratio of cancer insurance in Taiwan has exceeded 100%. In summary, the longevity risk can exist in two aspects: the probability of getting cancer increases as the insured live longer, and the life expansion after suffering from cancer is lengthened, increasing the overall medical cost.

The empirical analysis is based on the utilization of medical data of cancer patients from Taiwan's NHID. We first estimate the cancer incidence rates and post-cancer mortality rates and then apply stochastic models (such as the Lee-Carter model) to obtain the impact of mortality improvement and cancer incidence on the expected benefits of cancer insurance. Finally, we demonstrate how the natural hedging strategy can be applied to life insurers' longevity risk management by incorporating an additional death benefit in the original cancer insurance product.

The remainder of this paper is organized as follows. Section 2 describes the methodology of natural hedging, product design of cancer insurance, and mortality model used in this study. Section 3 presents the empirical analysis related to cancer insurance, including the estimates and forecasts of cancer incidence rates, post-cancer mortality rates, and non-cancer mortality rates. In Section 4, we demonstrate how the natural hedging strategy can effectively help insurers manage longevity risk. The conclusions and discussions are presented in Section 5.

2. Methodology

We first introduce the proposed (natural hedging) approach for cancer insurance. The natural hedging strategy on life insurance and annuity products has been widely discussed in recent years, and the original idea is that the values of life and annuity insurance policies move in the opposite direction when the mortality rates change (Cox and Lin, 2007; Wang et al., 2010).

The overall liability of a life insurer can remain nearly unchanged if the sales portfolio of life insurance and annuity policies are carefully arranged, but it is not easy in practice. Thus, instead of applying the natural hedging among different products, as proposed in Levantesi and Menzietti (2018), we implement a single insurance product strategy. A typical example would be an endowment product, which includes a death benefit if the insured dies during the policy term and a survival benefit if the insured is alive when the policy matures.

The key to applying the natural hedging approach in insurance products is that it contains two benefits groups, and their risks move in opposite directions over time. For whole-life cancer insurance in Taiwan, two insurance benefits are usually provided: one upon the insured being diagnosed with cancer for the first time, and the other upon the insured's death (with or without cancer). The increasing cancer incidence rates and decreasing mortality rates indicate that the two benefits move in the opposite direction, which will be discussed in the following sections. Increasing cancer incidence is not restricted to Taiwan and is quite common in Asian countries such as China, Japan, Singapore, and South Korea (Sun et al., 2020; Jung et al., 2019). Like the trend of mortality reduction, we expect that the trend of increasing cancer incidence would continue for these Asian countries, at least in the near future.

Cancer insurance in Taiwan often provides medical treatment and supplemental coverages (such as inpatient visits, outpatient days, surgeries, and sometimes survival benefits) after the insured is diagnosed with cancer and the incidence and death benefits mentioned previously. The survival rates of cancer patients seem to increase with time, and together with rising medical costs, we expect that the cost of medical and supplemental coverages would increase with time. In other words, the longevity risk becomes more serious if medical and supplemental coverages are included. The proposed approach can also be applied to cases where the policy includes other types of cancer benefits, although the estimations of related figures (e.g., pay-as-you-go medical cost) can be more complicated.

For the remainder of this section, we introduce the notation and formulas for calculating

the cost of cancer insurance. We assume that a healthy individual insured at age x purchases a single-premium whole-life cancer insurance policy that includes two types of cancer benefits: one that pays a fixed amount benefit when the insured is diagnosed with cancer for the first time, and the other that provides annuity payments/medical treatment for at most ten years after the insured is diagnosed with cancer. The calculation of the fixed cancer benefit, B_1, is similar to that of life insurance, and the actuarial present value can be expressed as

$$P_1 = B_1 \sum_{k=0} {}_k p_x \, {}_k p_x^* \, q_{x+k}^* v^{k+1} , \tag{1}$$

where ${}_k p_x$ is the probability of the healthy insured reaching age (x+k); q_{x+k}^* is the incidence rate of the insured being diagnosed with cancer for the first time at age (x+k); $v = \frac{1}{1+i}$ is the discount factor; and i is the interest rate.[2] ${}_k p_x^*$ is the probability of the insured reaching age (x+k) without having cancer and is equal to $(1 - q_x^*)(1 - q_{x+1}^*) \ldots (1 - q_{x+k-1}^*)$.

Similarly, the actuarial present value of the cancer annuity benefit that pays B_2 annually can be expressed as:

$$P_2 = B_2 \sum_{k=0} \left[{}_k p_x \cdot {}_k p_x^* \cdot q_{x+k}^* \sum_{i=0}^{9} {}_i p'_{x+k} v^{k+i+1} \right], \tag{2}$$

where ${}_i p'_{x+k}$ is the probability of the insured who has been diagnosed with cancer at age x+k reaching age x+k+i.

For the natural hedging, we consider the death benefit to offset the benefit of cancer incidence. Two types of death benefits can be provided: post-cancer death benefit and non-cancer death benefit. The post-cancer death benefit, B_3, is paid when the insured dies after he/she is diagnosed with cancer. The actuarial present value of the post-cancer death benefit is:

$$P_3 = B_3 \sum_{k=0} \left[{}_k p_x \cdot {}_k p_x^* \cdot q_{x+k}^* \sum_{i=0} {}_i p'_{x+k} q'_{x+k,i} v^{k+i+1} \right], \tag{3}$$

where $q'_{x+k,i}$ is the mortality rate of the insured at age x+k+i , given that he/she has cancer at

[2] For simplicity, we ignore the year-term in the expression of all actuarial notations and ${}_k p_x$ is the probability of the insured age x at year τ being alive at year (τ+k), where τ is the year of issuance.

age (*x+k)*.

The second death benefit, B_4, is for the case where the insured dies without cancer. The actuarial present value of the non-cancer death benefit is

$$P_4 = B_4 \sum_{k=0} {}_k p_x \, {}_k p_x^* \, q_{x+k} v^{k+1}, \tag{4}$$

where q_{x+k} is the mortality rate of the individual not diagnosed with cancer at age (*x+k)*.

One important theory in the literature regarding insurance purchase behavior is related to narrow framing, stating that consumers do not fully account for their needs or underestimate the probability of risk and are reluctant to buy insurance coverage. Gottlieb and Mitchell (2020) showed that Americans subject to narrow framing are substantially less likely to buy long-term care insurance than average. Furthermore, combining the two benefits in one product reduces the total administration cost. Thus, we believe that including non-cancer death benefits in cancer insurance reduces the insurer's risk and will be of the insured's interest. The insured is convinced that he/she will be able to collect the benefits in the future. However, if the insured have already had whole life insurance for death benefits, this would force them to purchase additional life insurance.

We use stochastic mortality models to evaluate the influence of changes in incidence rates and mortality on the cost of cancer insurance. Among all the models, we choose the Lee-Carter model (Lee and Carter, 1992) for simplicity and accuracy. It is assumed that the central death rate of an individual aged-*x* at year *t* satisfies:

$$\log(m_{x,t}) = \alpha_x + \beta_x \kappa_t + \varepsilon_{x,t}, \tag{5}$$

where the parameter α_x denotes the average age pattern of mortality over time; β_x denotes the deviations from the average pattern; κ_t is the variation in the level of mortality over time; and $\varepsilon_{x,t}$ is the error term.

The estimation of parameters is subject to two constraints:

$$\sum \kappa_t = 0 \quad \text{and} \quad \sum \beta_x = 1, \tag{6}$$

In addition, κ_t can be modeled by a random walk with drift process:

$$\kappa_t = \kappa_{t-1} + \phi + e_t \tag{7}$$

where $e_t \sim N(0, {\sigma_{LC}}^2)$ and ϕ is the drift parameter. Quite a few estimation methods are proposed for the Lee-Carter model, including the singular value decomposition, weighted least square, maximum likelihood estimation, or approximation method if there are missing data.

3. Statistical Analysis of the NHI Cancer Data

This study calculates cancer incidence rates and post-cancer mortality rates based on Taiwan's NHID first and then uses the Lee-Carter model to fit them. Taiwan launched the universal National Health Insurance (NHI) program in 1995. The NHI is a compulsory program covering all necessary medical services, including inpatient care, outpatient care, surgical treatment, and prescription drugs. At the end of 2020, more than 99.93% of Taiwanese were enrolled in the program.[3] The NHID thus provides a broad and complete set of medical data for empirical research, and researchers can acquire the use of the NHID if their applications are approved by the NHI Bureau.[4] The records of cancer-related medical utilization in NHID are close to census data, and all cancer patients receiving medical treatment via the NHI are included. The records of medical treatment not provided by the NHI (e.g., targeted therapy or molecularly targeted therapy) are not included in the NHID.

The NHI has been collecting medical utilization data since 1995, and the size of cancer-related data is approximately one TB, a big-data level database. Thus, we first apply the analysis skills of big data, such as data cleaning, and then compare the results with the official statistics, to double-check the data quality. For example, many researchers question the quality of the NHI data for the first few years of the NHI. We arrive at a similar conclusion and only use the NHI

[3] Gender Equality Committee of the Executive Yuan, https://gec.ey.gov.tw/Index.aspx

[4] Readers can refer to Yue et al. (2018) for a detailed description of the NHI Database.

data from 2005 to 2013. In addition, owing to the consideration of sample size, the cancer incidence and mortality rates estimated in this study are in the format of five age groups for both sexes (ages 0 to 84, separated into 17 five-age groups). The number of male/female cancer patients in Taiwan is close to 0.5 million.

Note that the NHID contains the medical records of all cancer patients, but their death records are incomplete. We adapt Yue et al. (2018) criteria to judge whether cancer patients are alive and then estimate the cancer-related incidence rates and mortality rates of cancer patients. The cancer patients are judged to be dead in year t if they have outpatient visits in year t and no visits in year t+1. Therefore, we cannot estimate the mortality rates of cancer patients in 2013. We can use the official number of cancer deaths to check whether the estimated number of cancer deaths is reasonable. The estimated number in 2005 is too small, and thus we only use the 2006–2012 data in this study. After data cleaning and death status judgment, we can only acquire the estimates of cancer incidence and post-cancer mortality rates for 2006–2012.

We first consider the estimated age-specific cancer incidence rates for the 17 five-age groups during the seven years. The cancer incidence rates are increasing functions of age for both sexes, and they reach a relative lowest value around ages 10–14 (Figure 2). In general, the male population has a higher cancer incidence rate than the female population. Taiwan's cancer incidence rate has been worsening in recent years, and the number of new cancer patients rises with time, increasing from less than 40,000 individuals in 2006 to more than 50,000 in 2012, which is approximately a 4% increment annually. However, the preceding increment is likely to be overestimated since Taiwan has been experiencing rapid population aging.

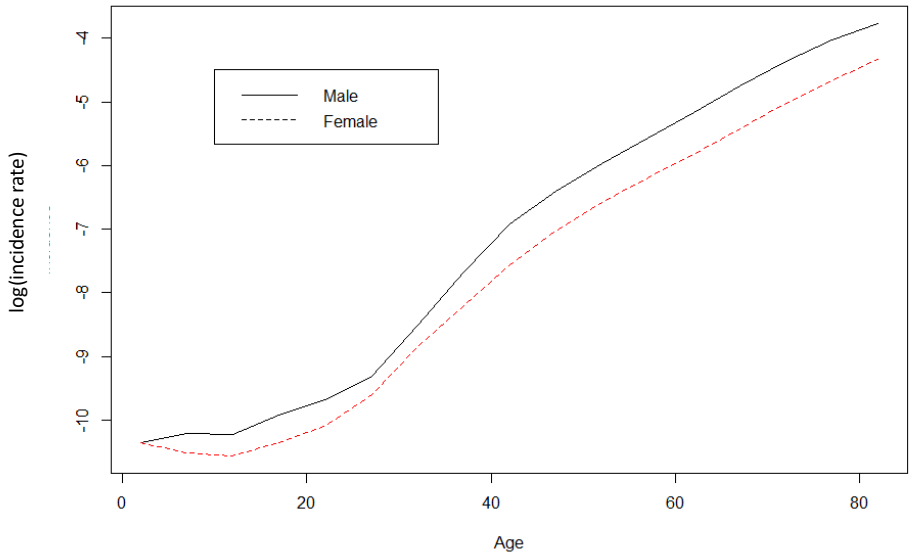

Figure 2. Cancer incidence rates from Taiwan's NHI Database (2006-2012)

There are many ways to deal with the factor of population aging, and using the idea of the standard mortality ratio (Brown, 1997) or mortality index is one of them. Conversely, stochastic models are a popular choice since they often provide accurate results for estimating and predicting cancer incidence and mortality rates. For the elderly groups, we first apply the incidence rates of ages 50 to 84 in the Gompertz law to estimate the cancer incidence rates among elderly groups. Then, we can either use a single stochastic model or a combination of relational and stochastic models (for example, the synthesis model by Su and Yue, 2019) to predict future incidence rates. We choose the Lee-Carter model in this study, and the annual increment of cancer incidence rates ranges between 1% and 2% for different ages. The fitting mean average percentage errors (MAPE) of applying the Lee-Carter model to male and female cancer incidence rates are 4.3% and 7.1%, close to those in Yue et al. (2018). The process for predicting non-cancer death mortality rates and post-cancer mortality rates are similar. We apply the Lee-Carter model separately for each of these three age-specific rates and obtain different sets of parameter estimates to acquire predictions.

We also calculate the mortality rates of cancer patients and those without cancer. We use

Taiwan's population mortality data from the Department of Interior (MOI) for the mortality rates of people without cancer since the NHID does not contain complete death records. Of course, we should remove the deaths owing to cancer, which is approximately 30% of all causes of death, since cancer-related deaths are included in the mortality rates for cancer patients. However, for simplicity, we treat the mortality rates from the MOI as the mortality rates for people without cancer.

We use Yue et al. (2018) criteria for the mortality rates of cancer patients. The sample size of cancer patients is not very large (approximately 200,000 for both males and females), and thus we apply graduation methods to smooth the mortality rates. In Taiwan, the Whittaker and kernel smoothing methods are often used to construct life tables, and we choose the Whittaker method in this study. Readers may refer to Yue et al. (2018) for a detailed discussion on choosing graduation methods for small populations. Figure 3 shows the mortality rates of cancer patients in 2006–2012. The mortality curve behaves differently between males and females. The male cancer-related mortality curves are very similar to those for regular causes of mortality, but those of females are U-shaped. The lowest mortality rates appear at ages 10–14 for males and 25–29 for females. The mortality improvement seems obvious for males and females, and we apply the Lee-Carter model to obtain the annual decrement. The parameters α_x and β_x vary by age and are constant in time. Conversely, κ_t is modeled by a random walk with a drift process, and its expectation is a linear function of time, that is, $\mathrm{E}(\kappa_t) = \kappa_0 + \phi t$. Thus, we can use $\phi\beta_x$ to represent the annual increment, or annual change rate, of mortality (or incidence) rate for age x. The mortality reduction of Taiwan's entire population is between 2% and 4% for different ages. The mortality reductions of cancer mortality rates are smaller than those of non-cancer mortality rates, and they are approximately 1%–2% annually.

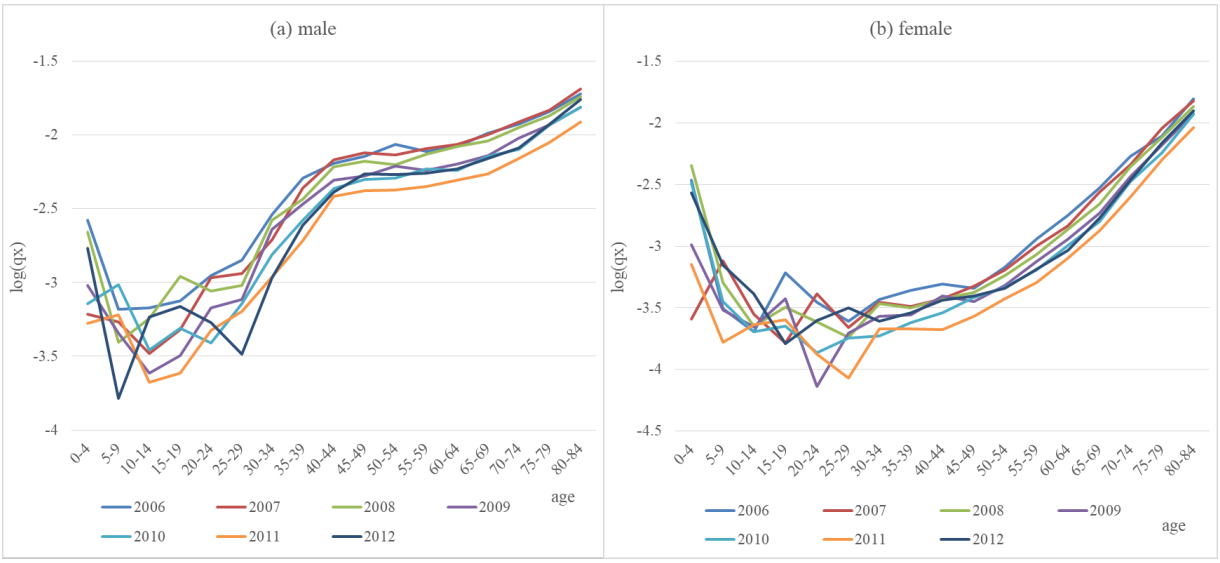

Figure 3. Mortality rates of cancer patients (2006–2012)

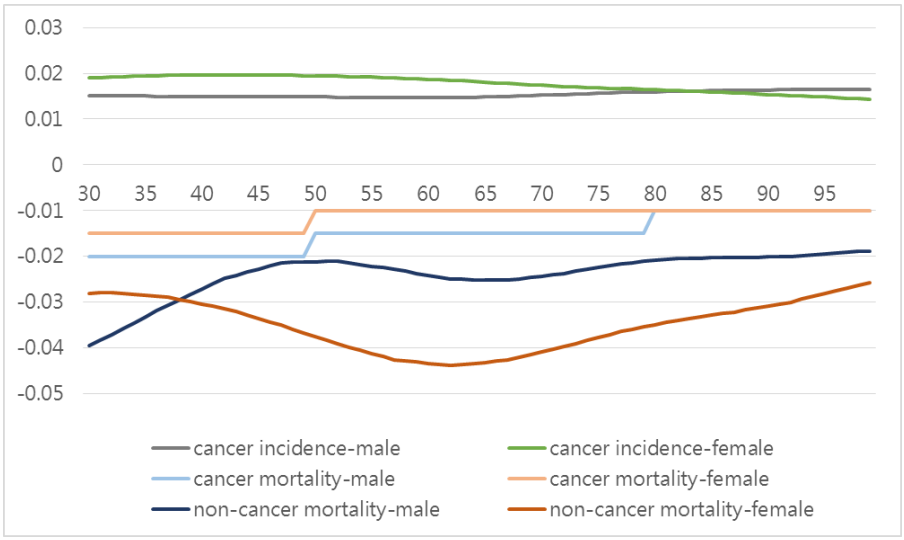

Figure 4. Annual average increment/reduction of cancer incidence and mortality rates

Based on the NHI data, the trends of cancer incidence rates and mortality rates (with or without cancer) are different, and they move in the opposite direction, similar to the trends in Yue et al. (2018). Figure 4 shows the annual average increment/decrement in cancer incidence and mortality rates for ages 30–99. Non-cancer mortality rates have the largest absolute percentage change, about twice the annual increment/reduction for the cancer incidence rates and cancer mortality rates. Increasing cancer incidence rates raise the cost of incurring cancer

benefits, whereas decreasing mortality rates reduce the cost of death benefits.[5] This creates the possibility of applying natural hedging for cancer insurance products; in the following section, we continue with the discussion of product design.

4. Cancer Insurance and the Natural Hedging

This section qualifies the longevity risk inherent in traditional cancer insurance products and illustrates whether natural hedging is a feasible approach. The basic idea of natural hedging is to reduce the overall risk by adjusting two types of benefits (or investments) whose performances are negatively correlated. Combing the life insurance and annuity benefits in the same policy is a very popular choice in the insurance business since decreasing mortality rates would reduce the benefit of life insurance but increase the annuity payment. Here, we will include the decreasing non-cancer and post-cancer death benefits to offset the increasing cancer benefits incurred by rising cancer incidence. We first apply the Lee-Carter model (Figure 4) to forecast the increment of cancer incidence rates and the decrement of (non-cancer and post-cancer) mortality rates, followed by evaluating the feasibility of implementing a natural hedge for cancer insurance.

Before exploring the influence of dynamic mortality/incidence rates on the cancer insurance premium, we should use the survival curve to explain the longevity risk of cancer insurance. For simplicity, suppose there are only four states for every individual: alive without cancer, death without cancer, alive with cancer, and death with cancer. We will use the case of men at age 30 to demonstrate the effect of increasing cancer incidence, assuming the number of survivors at age 30 is 10,000,000. Figure 5 displays the survival distributions of men at age 30 in the case of fixed cancer incidence rates (left panel) and the case of increasing cancer incidence rates (right panel). The light green part represents the healthy and alive population,

[5] Since the probability of incurring cancer and the survival probability of cancer patients are increasing, the cost of post-cancer medical benefits will also increase.

the gray part for those who die without cancer, the dark blue part for those with cancer and alive, and the light blue part for those who die with cancer.

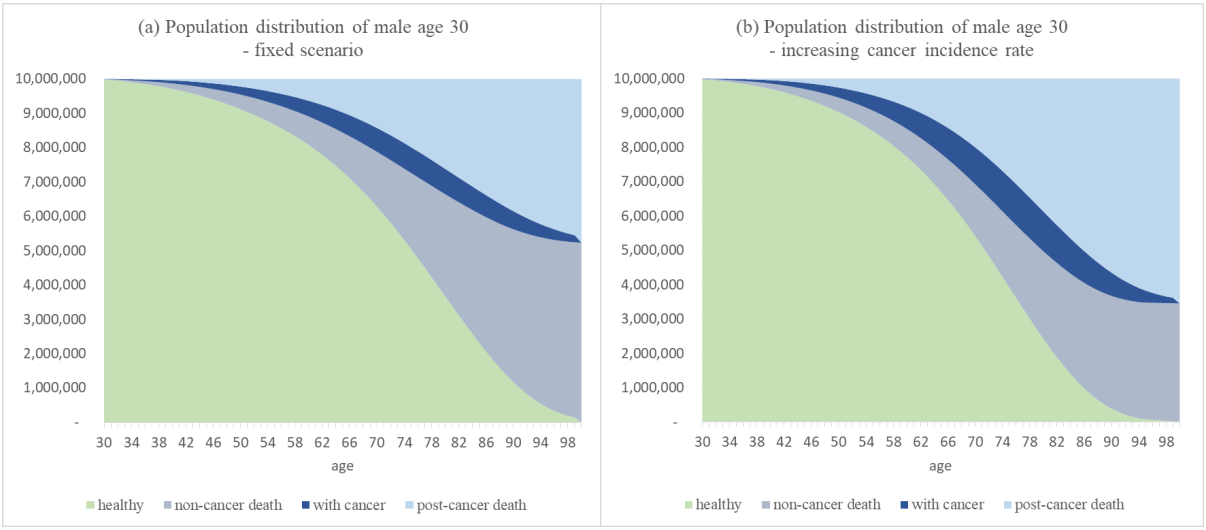

Figure 5. The survival distribution of men at age 30 under different assumptions

There are more survivors with cancer and more cancer deaths for any age in the case of increasing cancer incidence rates, and the differences in cancer survivors and cancer deaths between Figure 5(a) and 5(b) increase with age. This indicates that insurers have a higher cost (or longevity risk) if they issue long-term/whole-life cancer insurance products. Conversely, the number of non-cancer deaths is lower in Figure 5(b). This means that we can use non-cancer death benefits to offset the cancer benefits incurred by increasing cancer incidence. Likewise, the decreasing non-cancer and post-cancer mortality rates have a similar effect for balancing the increasing cancer benefits (though not shown here). The survival curves of females and different ages are similar.

Following the benefit design in the second section, the effects on the premium of the cancer incidence rate and post-cancer mortality rate can be classified in Table 1. To deal with the possible changes of future benefits due to the movement of risk factors in Table 1, we consider two types of cancer insurance (products A and B) to evaluate whether the idea of natural hedging is feasible to cope with the longevity risk. Product A provides a fixed lump-sum benefit when

the insured is diagnosed with cancer and provides a whole-life non-cancer death benefit. Product B provides a ten-year term annuity benefit after the insured is diagnosed with cancer and a fixed amount of post-cancer death benefit. We can express the premiums of products A and B as $P_A = P_1 + P_4$ and $P_B = P_2 + P_3$, respectively. Note that 2006 is treated as the baseline year, and the estimated cancer incidence rates and post-cancer/non-cancer mortality rates in 2006 are used to calculate the premiums. The annual increment/decrement via the Lee-Carter model is added to the values of the baseline year if there are mortality decreases or incidence increases.

Table 1. The effects on the premium of different risk factors

	Fixed cancer benefit (P_1)	Cancer annuity benefit (P_2)	Post-cancer death benefit (P_3)	Non-cancer death benefit (P_4)
Increasing cancer incidence rate	Rising	Rising	Rising	Decreasing
Decreasing post-cancer mortality rate	Unchanged	Rising	Decreasing	Unchanged

To simplify the discussion, we assume that the preceding benefits have approximately the same values and let B_1=10,000, B_2=1,000, B_3=10,000, and B_4=10,000. We then use the values derived via the Lee-Carter model and calculate the single premiums of both products for insured ages of 30, 40, 50, 60, and 70 with a 2% interest rate. Based on the assumption that the variations over time (κ_t^c for cancer incidence rate, $\kappa_t^{c\_death}$ for post-cancer mortality rate, and $\kappa_t^{nc\_death}$ non-cancer mortality rate) are modeled by a random walk with drift process, we further assume mutual independence and calculate the premium by simulating each path 10,000 times. The detailed values of the simulated results, including the mean and standard deviation of the premium amounts, are presented in Appendix A.

First, we investigate the pricing risk that underlies products A and B. Pricing risk refers to

the possibility that life insurers might underestimate future benefit payments. We will use measures of variation, such as variance and coefficient of variation, to evaluate the risk. We start with the simulation results for product A (Figure 6), and the height of the distribution peak can be treated as the reciprocal of the variance. Combining the two benefits in product A creates a smaller variance/standard deviation, and the variance of premium P_1+P_4 distribution is approximately 20% or less of those for premium P_1 and P_4 distributions. The detailed (mean and standard deviation) results of P_1, P_4, and P_1+P_4 for different issued ages are in Appendix A-I, and product A has smaller standard deviations. The outcomes of coefficient of variation (CV) show similar results (Table 2), and product A (or P_1+P_4) has smaller CV values. The risk is substantially lower after combining the two benefits, especially for the older age group. It seems that using the non-cancer death benefit that moves in the opposite direction to offset the increasing trend of cancer incidence rates is a possible choice for natural hedging.

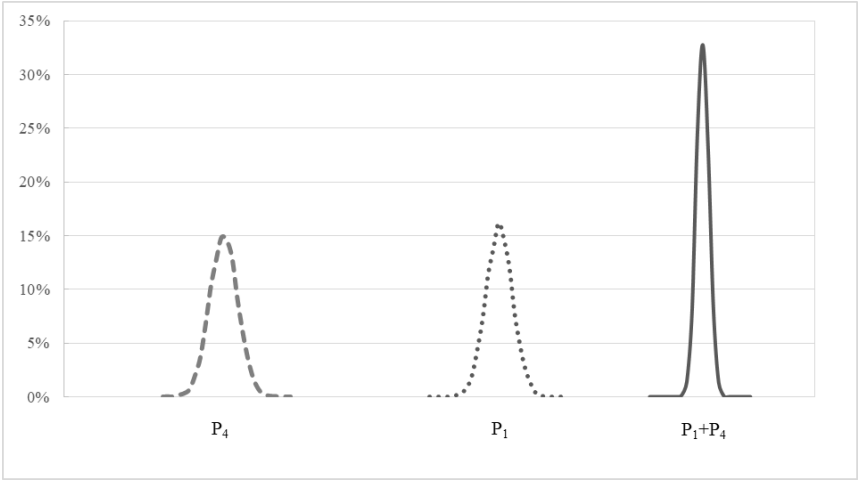

Figure 6. Premium distribution for product A (male age 30)

Table 2: The coefficient of variation of Product A (%)

age	Male			Female		
	P_1	P_4	P_1+ P_4	P_1	P_4	P_1+ P_4
30	0.0722	0.2928	0.0260	0.0685	0.1592	0.0275
40	0.0754	0.2430	0.0222	0.0643	0.1200	0.0202
50	0.0780	0.1946	0.0187	0.0595	0.0862	0.0146
60	0.0767	0.1445	0.0152	0.0556	0.0592	0.0105

70	0.0715	0.0943	0.0106	0.0495	0.0354	0.0073

The simulation results for product B are not the same as those for product A. Combining the coverages of P_2 and P_3 in product B, on the contrary, has a larger variance/lower peak (Figure 7 and Appendix A-II) but smaller CV values (Table 3), indicating that product B does not necessarily decrease the pricing risk for life insurers. In other words, the fact that the cancer incidence rates increase and post-cancer mortality rates decrease does not guarantee a smaller risk for P_2+P_3 since the cancer annuity and post-cancer death benefit move in the same direction as the cancer incidence rates increase/decrease. We need to include another benefit to offset the increase in cancer incidence, and similar to product A, we consider adding a non-cancer death benefit. The result is better, as we see that the peak of the P_2+P_3+P_4 distribution is higher than those of the P_2, P_3 and P_2+P_3 distributions, i.e., including non-cancer death benefits create smaller variations (e.g., variance and CV).

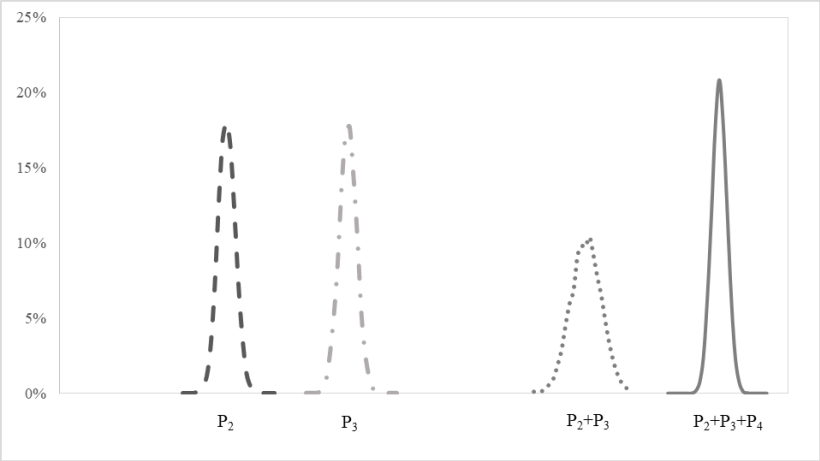

Figure 7. Premium distribution for product B (male 30)

Table 3: The coefficient of variation of Product B (%)

age	Male				Female			
	P_2	P_3	P_2+ P_3	P_2+ P_3+ P_4	P_2	P_3	P_2+ P_3	P_2+ P_3+ P_4
30	0.0936	0.0760	0.0736	0.0312	0.0867	0.0711	0.0698	0.0408
40	0.0918	0.0787	0.0753	0.0274	0.0802	0.0671	0.0658	0.0332
50	0.0906	0.0793	0.0772	0.0227	0.0760	0.0617	0.0618	0.0252
60	0.0854	0.0782	0.0772	0.0175	0.0713	0.0568	0.0569	0.0177
70	0.0754	0.0719	0.0707	0.0121	0.0640	0.0503	0.0495	0.0108

Based on the results of premium distribution for products A and B, we believe that natural hedging is a feasible approach for dealing with the (longevity and pricing) risk for cancer insurance. However, product design is crucial, and product B is a good example. Simply choosing two benefits moving in opposite directions does not promise a smaller pricing risk. It seems that the size of the death benefit is the key in product design. In addition to the premium distribution, we then conduct a sensitivity analysis on the changes in cancer incidence rates and post-cancer mortality rates over time, κ_t^c and $\kappa_t^{c\_death}$. In particular, we aim to explore the influence of unexpected changes regarding cancer incidence rates and post-cancer mortality rates on insurance premiums.

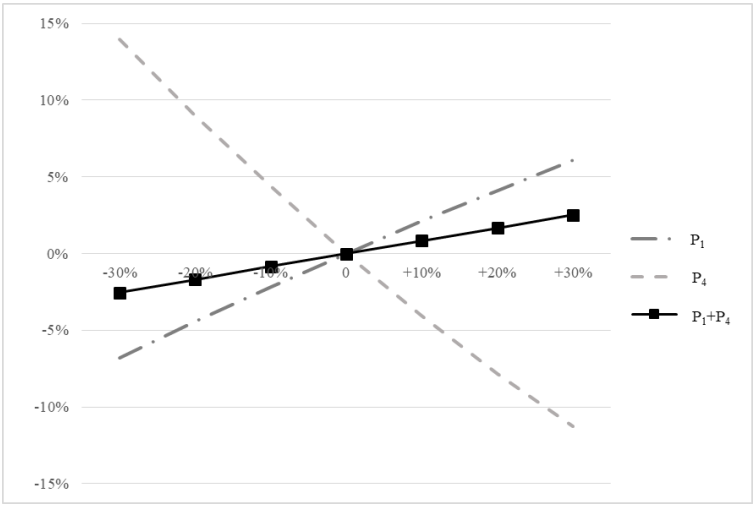

Figure 8. Sensitivity analysis cancer incidence κ_t^c (male 30)

This study uses the Lee-Carter model to predict the cancer incidence and mortality rates, which indicates that the time parameter κ_t plays a key role. Thus, we use the changes in κ_t for the sensitivity analysis. Suppose the cancer incidence and post-cancer mortality rates increase slower/faster than expected; for example, we assume that the time parameters are $\alpha\kappa_t^c$ and $\alpha\kappa_t^{c\_death}$ with $0.7 \leq \alpha \leq 1.3$. Again, we use the case of a male insured at age 30 as an example. We first consider the case of unexpected changes in cancer incidence rates and their influence on P_1, P_2, P_3, and P_4 (Appendix B-I). We found that P_4 is the most sensitive, and P_3 is

the least sensitive to the unexpected change in cancer incidence rates for all ages. We further consider the influence of $\alpha\kappa_t^c$ on the premium of product A (Figure 8), and P_1+P_4 is less sensitive than P_1 and P_4. This means that product A is more stable regarding the variation in premium distribution and premium fluctuation dealing with the unexpected change in cancer incidence rates. In other words, combining fixed cancer benefits and non-cancer death benefits is a feasible approach.

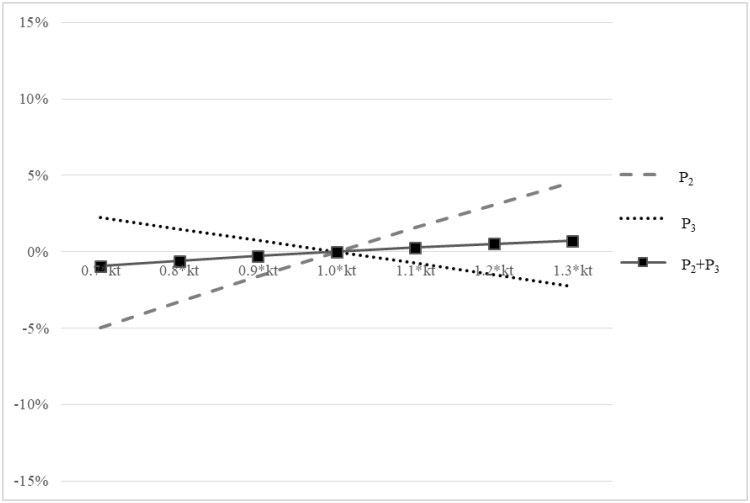

Figure 9. Sensitivity analysis of post-cancer mortality $\kappa_t^{c\_death}$ (male 30)

The results of the sensitivity analysis for unexpected changes in post-cancer mortality rates are shown in Appendix B-II. Unlike the case of κ_t^c, unexpected changes in $\kappa_t^{c\_death}$ only has an influence on cancer annuity and post-cancer benefit, or P_2 and P_3. P_2 is more sensitive to the change in $\kappa_t^{c\_death}$, and P_2 and P_3 change in opposite directions for all ages. We also consider the influence of $\alpha\,\kappa_t^{c\_death}$ on the premium of product B (Figure 9), and P_2+P_3 is less sensitive than P_2 and P_3. Although the premium distribution of P_2+P_3 has a larger variance, product B has a smaller CV for the P_2+P_3 distribution and is less sensitive to unexpected changes in $\kappa_t^{c\_death}$. We believe that product B is a practical product design for cancer insurance, with suitable modifications. The results of the sensitivity analysis clearly demonstrate that natural hedging can be a feasible solution for insurers to deal with the longevity risk in cancer insurance. By

further choosing a suitable benefits combination, the slope of the mixed products (P1+P4 and P2+P3) in both Figure 8 and 9 can approach 0.

5. Conclusion and Discussions

Prolonging life spans have been a common phenomenon since the second half of the 20th century, and in many countries, longevity risk is a major concern. However, the longevity risk should not be restricted to public pension plans or commercial annuity products, and it needs to be considered in health insurance and other types of insurance. Here, we study the impact of longevity risk on Taiwan's cancer insurance based on Taiwan's NHID and propose a natural hedging approach to deal with it. We found that it is possible to offset the longevity risk via natural hedging based on cancer or non-cancer death benefit that moves in the opposite direction to offset the increasing trend of cancer incidence rates. However, the cancer death benefit alone is not good enough and we need to include the non-cancer death benefit.

One of the advantages of the proposed approach is that we diversified the longevity risk in a single insurance policy. The traditional natural hedging approach requires a balanced amount of sales between two different life/annuity products, challenging to implement. As the proportion of the elderly population increases, we expect that there will be more demand for annuity and health insurance, which has already surpassed that of life insurance. The approach proposed in this study can be applied to other insurance products if there are two or more benefits, and the costs of these benefits are negatively correlated. Endowment insurance products are a good example of our approach, and they can be extended to combinations of life, annuity, health, and even long-term care insurance.

The natural hedging approach also faces the problem of feasibility. If the non-cancer death benefit is larger than that of cancer benefits, this will not be practical for cancer and other health insurance products. Nonetheless, we think the natural hedging approach provides new possibilities. Instead of relying on only one approach, we can combine natural hedging and

other approaches, such as derivatives for cancer- or mortality-related risk. The non-cancer death benefit included in the product can reduce the influence of increasing cancer costs in cases where the longevity risk is more severe than expected.

Of course, data quality and availability are critical in applying our approach. In addition to updating and maintaining data, data analysis becomes more complicated if more insurance plans are involved. In our case, the cancer claim data from Taiwan's NHID is about the size of one TB, which is a task for big data teams. It took us more than half a year to clean and pre-process the cancer data, even though we have more than ten years of experience in analyzing NHI data. We expect that the need for analyzing big data in the insurance industry will grow with time, and thus, insurance companies will need to hire and train big data-related experts (e.g., data scientists and information security engineers), in addition to doctors.[6]

There are more than 50 years of reliable mortality data in Taiwan, but the length of cancer data available is slightly shorter (since 1981). The reporting records on cancer have become more stable and complete in recent years, and it is usually suggested that data should not be used before 2000. As the annual increment in cancer incidence is between 1% and 2%, it would take more than 30 years to double the cancer incidence at this scale of increment. Nevertheless, we believe that these data can provide stable predictions for cancer incidence. However, we only use 7-year data (of incidence and mortality rates) for prediction, and the data period is too short. In addition, the non-cancer mortality rates are from the MOI, but the mortality rates for eliminated cancer causes should be lower than those of all causes of death, approximately 70% of the MOI values. Readers must consider these limitations when applying the findings of this study.

The medical utilization of cancer patients is even more limited, and it would not be appropriate to apply stochastic models for predicting cancer incidence and medical costs. This

[6] In 2018, the Society of Actuaries in the U.S. started a new exam, Predictive Analytics, which can be treated as a first step to the big data era.

creates challenges in using the proposed natural hedging method. Conversely, we use medical records to determine whether cancer patients are still alive. Although the total number of estimated post-cancer deaths is close to that of official statistics, it is possible to improve the accuracy of estimations. The Taiwanese government now allows researchers to link the NHID with official death records, and thus, we can acquire the estimated mortality rates for ages 85 and above.[7]

[7] There was no such service when we applied the usage of NHID in 2015.

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Appendix A: Simulation Results of Single Premium for Cancer Insurance

The following tables present the simulation results of premium amounts for all types of whole-life cancer insurance products considered in this study.

I. Product A: Lump-sum cancer benefit (10,000) and non-cancer death benefit (10,000)

age		Male			Female		
		P_1	P_4	P_1+P_4	P_1	P_4	P_1+P_4
30	Mean	3,516.55	904.94	4,421.49	3,287.45	785.56	4,073.02
	Std.	2.55	2.66	1.14	2.23	1.23	1.12
40	Mean	3,872.74	1316.74	5,189.48	3,483.60	1,225.26	4,708.86
	Std.	2.94	3.22	1.14	2.19	1.45	0.95
50	Mean	4,142.31	1854.85	5,997.16	3,496.34	1,903.39	5,399.74
	Std.	3.21	3.64	1.12	2.08	1.64	0.79
60	Mean	4,222.79	2628.96	6,851.75	3,289.24	2,920.95	6,210.19
	Std.	3.25	3.82	1.03	1.84	1.73	0.65
70	Mean	4,053.31	3647.57	7,700.89	2,850.83	4,297.88	7,148.71
	Std.	2.89	3.41	0.81	1.40	1.55	0.53

II. Product B: Cancer annuity (1,000/year, maximum ten years) and post-cancer death benefit (10,000)

age		Male			Female		
		P_2	P_3	P_2+P_3	P_2	P_3	P_2+P_3
30	Mean	2,305.50	2,925.08	5,230.58	2,350.72	2,565.77	4916.49
	Std.	2.13	2.24	3.85	2.01	1.79	3.44
40	Mean	2,414.57	3,292.93	5,707.50	2,373.49	2,814.59	5188.08
	Std.	2.23	2.61	4.39	1.91	1.83	3.38
50	Mean	2,449.02	3,592.45	6,041.47	2,228.53	2,935.10	5163.63
	Std.	2.20	2.87	4.71	1.67	1.81	3.16
60	Mean	2,344.74	3,733.80	6,078.55	1,909.66	2,867.35	4777.00
	Std.	2.00	2.95	4.68	1.36	1.65	2.74
70	Mean	2,080.75	3,653.55	5,734.31	1,451.94	2,571.82	4023.76
	Std.	1.58	2.65	4.07	0.94	1.29	2.02

Appendix B: Sensitivity Analysis

I. Sensitivity analysis on the premiums, P_1, P_2, P_3, and P_4. The following table shows the percentage change of premium amount based on -30%, -20%, -10%, +10%, +20%, and +30% changes in the variations over time of cancer incidence rate, κ_t^c.

Insured age: 30	Male				Female			
	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	-7.03%	-7.99%	-6.66%	13.07%	-10.37%	-11.50%	-10.03%	20.63%
$0.8\kappa_t^c$	-4.56%	-5.18%	-4.31%	8.64%	-6.81%	-7.56%	-6.57%	14.16%
$0.9\kappa_t^c$	-2.21%	-2.52%	-2.09%	4.28%	-3.35%	-3.72%	-3.23%	7.29%
$1.1\kappa_t^c$	2.08%	2.37%	1.96%	-4.15%	3.24%	3.61%	3.10%	-7.70%
$1.2\kappa_t^c$	4.04%	4.60%	3.79%	-8.15%	6.35%	7.09%	6.07%	-15.82%
$1.3\kappa_t^c$	5.88%	6.70%	5.50%	-11.96%	9.33%	10.44%	8.90%	-24.33%

Insured age: 40	Male				Female			
	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	-6.13%	-6.88%	-5.91%	9.99%	-8.59%	-9.35%	-8.48%	13.50%
$0.8\kappa_t^c$	-4.00%	-4.49%	-3.86%	6.66%	-5.68%	-6.18%	-5.60%	9.22%
$0.9\kappa_t^c$	-1.96%	-2.20%	-1.89%	3.32%	-2.81%	-3.06%	-2.77%	4.72%
$1.1\kappa_t^c$	1.88%	2.11%	1.80%	-3.30%	2.75%	3.01%	2.71%	-4.96%
$1.2\kappa_t^c$	3.67%	4.12%	3.52%	-6.55%	5.44%	5.95%	5.35%	-10.15%
$1.3\kappa_t^c$	5.38%	6.04%	5.15%	-9.73%	8.07%	8.82%	7.91%	-15.57%

Insured age: 50	Male				Female			
	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	-5.11%	-5.65%	-5.00%	7.20%	-6.93%	-7.40%	-6.90%	8.06%

$0.8\kappa_t^c$	-3.36%	-3.72%	-3.29%	4.82%	-4.60%	-4.92%	-4.58%	5.48%
$0.9\kappa_t^c$	-1.66%	-1.83%	-1.62%	2.42%	-2.29%	-2.45%	-2.28%	2.79%
$1.1\kappa_t^c$	1.61%	1.78%	1.57%	-2.43%	2.27%	2.42%	2.26%	-2.91%
$1.2\kappa_t^c$	3.18%	3.51%	3.10%	-4.87%	4.51%	4.82%	4.49%	-5.92%
$1.3\kappa_t^c$	4.69%	5.19%	4.57%	-7.30%	6.72%	7.20%	6.68%	-9.05%

Insured	Male				Female			
age: 60	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	-4.01%	-4.39%	-3.95%	4.56%	-5.27%	-5.57%	-5.26%	4.24%
$0.8\kappa_t^c$	-2.65%	-2.90%	-2.62%	3.06%	-3.51%	-3.71%	-3.51%	2.87%
$0.9\kappa_t^c$	-1.32%	-1.44%	-1.30%	1.54%	-1.75%	-1.85%	-1.75%	1.45%
$1.1\kappa_t^c$	1.30%	1.42%	1.28%	-1.56%	1.75%	1.85%	1.75%	-1.50%
$1.2\kappa_t^c$	2.57%	2.81%	2.53%	-3.12%	3.49%	3.69%	3.49%	-3.04%
$1.3\kappa_t^c$	3.83%	4.18%	3.77%	-4.71%	5.23%	5.52%	5.22%	-4.63%

Insured	Male				Female			
age: 70	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	-2.88%	-3.16%	-2.85%	2.50%	-3.58%	-3.80%	-3.57%	1.88%
$0.8\kappa_t^c$	-1.91%	-2.10%	-1.89%	1.68%	-2.39%	-2.53%	-2.38%	1.27%
$0.9\kappa_t^c$	-0.95%	-1.05%	-0.94%	0.85%	-1.20%	-1.27%	-1.19%	0.64%
$1.1\kappa_t^c$	0.95%	1.04%	0.94%	-0.85%	1.20%	1.27%	1.20%	-0.65%
$1.2\kappa_t^c$	1.89%	2.08%	1.87%	-1.72%	2.40%	2.54%	2.39%	-1.32%
$1.3\kappa_t^c$	2.83%	3.10%	2.80%	-2.59%	3.60%	3.81%	3.59%	-2.00%

II. Sensitivity analysis of the premiums P_1, P_2, P_3, and P_4. The following table shows the percentage change in premium amount based on -30%, -20%, -10%, +10%, +20%, and +30% changes in the variations over time of post-cancer mortality rate, $\kappa_t^{c\_death}$.

Insured age: 30	Male				Female			
	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	0.00%	-5.11%	2.20%	0.00%	0.00%	-3.76%	2.45%	0.00%
$0.8\kappa_t^c$	0.00%	-3.33%	1.48%	0.00%	0.00%	-2.44%	1.65%	0.00%
$0.9\kappa_t^c$	0.00%	-1.63%	0.75%	0.00%	0.00%	-1.19%	0.83%	0.00%
$1.1\kappa_t^c$	0.00%	1.55%	-0.76%	0.00%	0.00%	1.13%	-0.83%	0.00%
$1.2\kappa_t^c$	0.00%	3.03%	-1.53%	0.00%	0.00%	2.20%	-1.67%	0.00%
$1.3\kappa_t^c$	0.00%	4.44%	-2.31%	0.00%	0.00%	3.21%	-2.51%	0.00%

Insured age: 40	Male				Female			
	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	0.00%	-4.34%	1.57%	0.00%	0.00%	-3.45%	1.79%	0.00%
$0.8\kappa_t^c$	0.00%	-2.85%	1.06%	0.00%	0.00%	-2.26%	1.20%	0.00%
$0.9\kappa_t^c$	0.00%	-1.40%	0.53%	0.00%	0.00%	-1.11%	0.60%	0.00%
$1.1\kappa_t^c$	0.00%	1.35%	-0.54%	0.00%	0.00%	1.06%	-0.61%	0.00%
$1.2\kappa_t^c$	0.00%	2.65%	-1.09%	0.00%	0.00%	2.08%	-1.23%	0.00%
$1.3\kappa_t^c$	0.00%	3.91%	-1.65%	0.00%	0.00%	3.05%	-1.84%	0.00%

Insured age: 50	Male				Female			
	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	0.00%	-3.51%	1.06%	0.00%	0.00%	-3.15%	1.23%	0.00%
$0.8\kappa_t^c$	0.00%	-2.31%	0.71%	0.00%	0.00%	-2.07%	0.83%	0.00%

$0.9\kappa_t^c$	0.00%	-1.14%	0.36%	0.00%	0.00%	-1.02%	0.42%	0.00%
$1.1\kappa_t^c$	0.00%	1.11%	-0.36%	0.00%	0.00%	0.99%	-0.42%	0.00%
$1.2\kappa_t^c$	0.00%	2.20%	-0.73%	0.00%	0.00%	1.95%	-0.84%	0.00%
$1.3\kappa_t^c$	0.00%	3.26%	-1.10%	0.00%	0.00%	2.88%	-1.27%	0.00%

Insured	Male				Female			
age: 60	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	0.00%	-2.65%	0.65%	0.00%	0.00%	-2.78%	0.78%	0.00%
$0.8\kappa_t^c$	0.00%	-1.75%	0.44%	0.00%	0.00%	-1.84%	0.52%	0.00%
$0.9\kappa_t^c$	0.00%	-0.87%	0.22%	0.00%	0.00%	-0.91%	0.26%	0.00%
$1.1\kappa_t^c$	0.00%	0.86%	-0.22%	0.00%	0.00%	0.89%	-0.26%	0.00%
$1.2\kappa_t^c$	0.00%	1.70%	-0.45%	0.00%	0.00%	1.76%	-0.53%	0.00%
$1.3\kappa_t^c$	0.00%	2.53%	-0.67%	0.00%	0.00%	2.61%	-0.80%	0.00%

Insured	Male				Female			
age: 70	P_1	P_2	P_3	P_4	P_1	P_2	P_3	P_4
$0.7\kappa_t^c$	0.00%	-1.81%	0.35%	0.00%	0.00%	-2.26%	0.43%	0.00%
$0.8\kappa_t^c$	0.00%	-1.20%	0.23%	0.00%	0.00%	-1.50%	0.29%	0.00%
$0.9\kappa_t^c$	0.00%	-0.60%	0.12%	0.00%	0.00%	-0.74%	0.14%	0.00%
$1.1\kappa_t^c$	0.00%	0.59%	-0.12%	0.00%	0.00%	0.73%	-0.14%	0.00%
$1.2\kappa_t^c$	0.00%	1.18%	-0.24%	0.00%	0.00%	1.46%	-0.29%	0.00%
$1.3\kappa_t^c$	0.00%	1.76%	-0.36%	0.00%	0.00%	2.17%	-0.44%	0.00%