

## Background

Long Term Care is a relatively newer insurance product. Especially when compared to life insurance which was first offered in Britain, in the 16<sup>th</sup> century (Simon, n.d.). By contrast, Long Term Care (“LTC”) came to the market in the 1970s (Brewster & Gutterman, 2014). Because LTC is a newer product, there is naturally less data, especially at older ages. Further, the LTC product has undergone product variations. This influences the types of people who purchase LTC, making data analysis on the product more challenging (Eaton & Morton, 2022). In addition, LTC has become significantly more expensive due to rate increases and lack of supply on the carrier side. It is possible that current LTC policyholders are more affluent than in the 1970s and 1980s. In addition to making LTC cost prohibitive, rate increases can lead to anti-selection. Anti-selection after a rate increase by influencing healthier people to lapse their policies as they may feel they will not need their LTC benefits (Bluhm & Leida, 2015). In addition, to data challenges, LTC is naturally more subjective than life insurance. It is more subjective because we are comparing the determination of if someone is disabled versus determining if someone is alive, a binary event.

When accessing LTC, actuaries need to develop all sorts of assumptions to project the future benefits paid out to policyholders. Arguably, the biggest assumption is the incidence rate which represents the rate at which people go from being active to receiving LTC benefits. The higher the incidence rate, the worse off the insurance company (and the policyholder). In addition, there are two mortality rates which will be the focus of this paper: active mortality and disabled mortality. The insurance company benefits when both are high (policyholder does not benefit) as evidenced by the next two arguments. When a person dies while paying premiums, the LTC insurer owes nothing to the insured and keeps the past premiums collected. When someone dies while on claim, the LTC carrier stops paying the policyholder benefits.

Now, the active mortality rate can be difficult to determine because the insured has little incentive to report active deaths to the insurer. The insurer would just know the person stopped paying premium (Brewster & Gutterman, 2014). Typically, insurers have relied on the social security master death file to verify/adjust their death counts. However, this source appears to have become less accurate in recent times (Brewster & Gutterman, 2014; Rose, 2013). For disabled mortality, insurers have an incentive to monitor claims scrupulously so that they do not pay out overpay on benefits. So, it is likely disabled mortality is more precise than active mortality. To combat issues in measuring active mortality, actuaries sometimes assume a total mortality framework. They assume the total mortality (active and disabled mortality combined) will equal some industry mortality table. By definition, total mortality is the weighted average of the active mortality rate and the disabled mortality rate, as seen below.

*Let:  $q_x^t$  = total mortality rate for age  $x$ ;  $q_x^a$  = active mortality rate for age  $x$ ;*

*$q_x^d$  = disabled mortality rate for age  $x$ ;*

*$w_1(x)$  = percent of population that is active at the start of age  $x$ ;*

*$w_2(x)$  = percent of population that is disabled at the start of age  $x$ ;*

$$\Rightarrow w_1(x) + w_2(x) = 1$$

$$\Rightarrow q_x^t = w_1(x) * q_x^a + w_2(x) * q_x^d$$

Where this gets interesting is the w's, the percent of the population that is active or disabled. The incidence rate influences the w's as incidence drives more people to the disabled status. In turn, this would shift the total mortality curve up. However, active mortality would need to come down to compensate in order to preserve total mortality. Now, I would be dishonest if I did not mention that there are other factors at play here including lapses, claim exhaustions<sup>1</sup>, and recoveries. However, for this analysis, I will limit my analysis of these decrements and make simplifying assumptions.

Now, based on the equations above and conceptual knowledge, we can make the following conclusions. Higher incidence leads to a higher  $w_2(x)$  and since  $q_x^d \geq q_x^t \geq q_x^a$ , that means higher incidence would push total mortality up<sup>2</sup>. To preserve total mortality either active mortality or disabled mortality (or both) would have to come down. Either option is adverse to the insurance company. Now, I could conclude here, with the implication that higher incidence, in addition to leading to more claims, has a compounding effect when following the total mortality framework. This is not debatable as dictated by the equations above. However, I believe that walking through a practical example better drives the point home.

For the remainder of this paper, I will cover the following in order.

- LTC Decrement Curves
- Methodology
- Analysis
- Conclusions

## LTC Decrement Curves

A decrement is the rate at which a population change occurs. In this case, the two main population changes include deaths (active or disabled deaths) and incidence (shifting from active to disabled population). In general, it is important to measure decrements consistently with how one models the decrements. In the multi-decrement model for LTC, one may assume that the decrements add together (meaning rates are calculated with the same denominator) or multiply together (i.e., ending lives = (beginning lives) \* (1-death rate) \* (1-incidence rate)). There are, of course, other ways to develop assumptions, but these two mentioned are the most foundational. See Appendix 1, for numerical examples<sup>3</sup>.

In general, as you might expect, mortality rises exponentially with age. The graph below shows a fairly popular mortality table for annuities, the 2012 individual annuity mortality ("IAM") table.

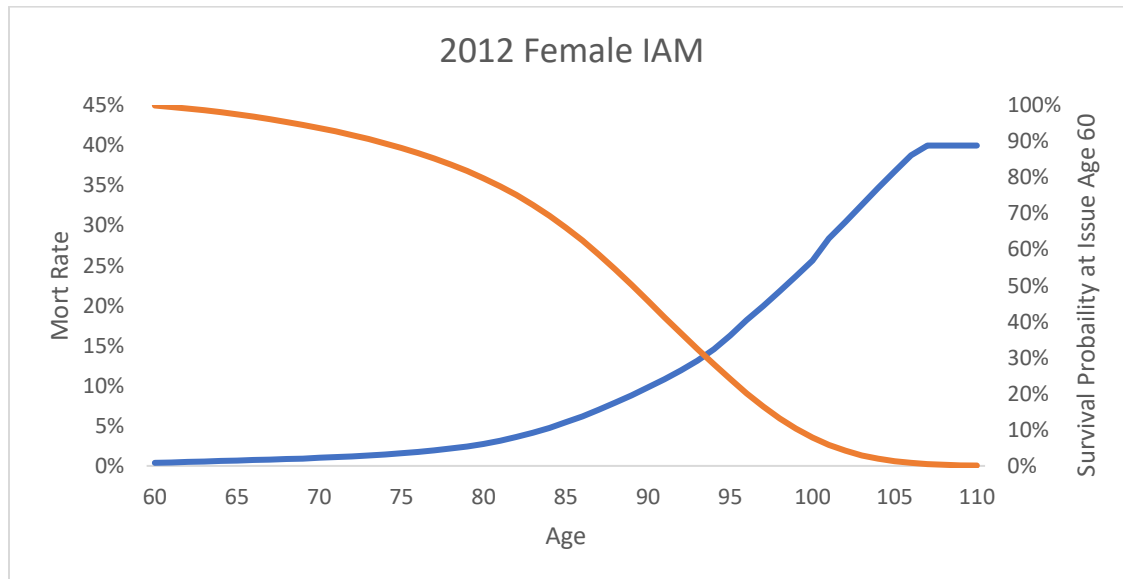
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<sup>1</sup> Claim exhaustions occur when policy ends because the policyholder received the maximum amount of long-term care benefits.

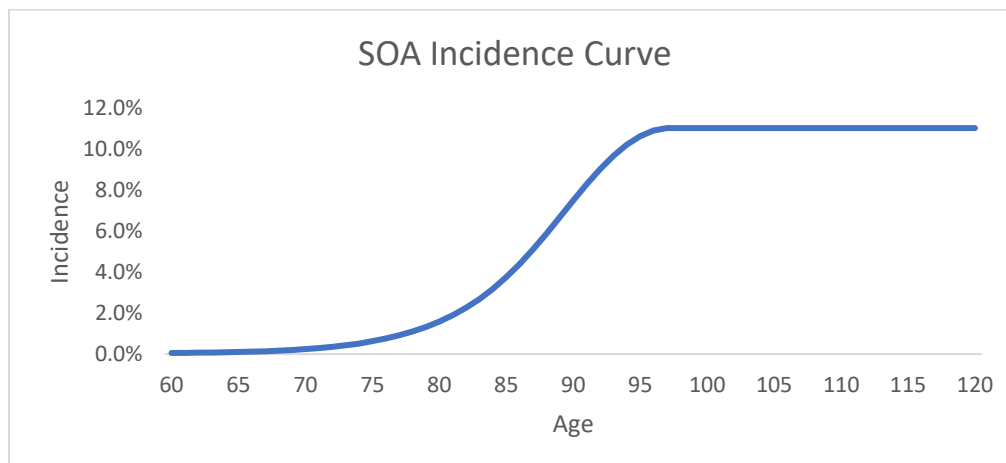
<sup>2</sup> If more people are disabled than mortality would be higher all else equal since more people would be attributed with disabled mortality which is higher than active mortality.

<sup>3</sup> And more precise jargon than "additive" and "multiplicative".

The blue line is the mortality rate for each age and orange line is probability of surviving to a certain age given the person was issue age 60. The mortality rate is exponential until age 105 where the developers of the table set mortalities rates to 40% thereafter. The lack of data at extremely old ages (i.e. 105+) may have been a reason for this assumption. A key reason why data is lacking for 100+ is because few people live into those ages as evidenced by the the orange line.



For incidence, there is less of a consensus on what the incidence curve looks like. The incidence rate may vary significantly by company (Eaton & Morton, 2022). Further, compared to deaths, incidence is not as clearly a biological event. A doctor typically needs to verify that a person cannot perform 2 of the 6 activities of daily living or has cognitive impairment (HIPPA, 1996; Eaton & Morton, 2022). This test naturally makes incidence subjective. Further, incidence may also be affected by a company’s claim adjudication procedures, the broader economy, and likely other factors. Below is an incidence table (“Model 2”) from the 2015 study “Long Term Care Experience Basic Table Development”. Incidence rises exponentially from age 80 to 95 and then it appears to level off at around 11% for ages 97+.



## Methodology

This section documents the methodology and assumptions used in the analysis. This analysis follows a group of 1,000 60-year-old women through time. Below is the key equation presented previously.

$$q_x^t = w_1(x) * q_x^a + w_2(x) * q_x^d$$

In addition, to solve for  $w_1(x)$  and  $w_2(x)$ , we need to calculate the number of active and disabled lives which will be referred to as  $W_1(x)$  and  $W_2(x)$  respectively.

$$w_1(x) = \frac{W_1(x)}{W_1(x) + W_2(x)} \Rightarrow w_2(x) = 1 - w_1(x)$$

$$\text{Let: } W_1(x) = W_1(x-1) - W_1(x-1) * d(x) - W_1(x-1) * q_x^a + W_2(x-1) * \text{rec}(x)$$

Where  $d(x)$  = is incidence rate at age  $x$  and  $\text{rec}(x)$  = recovery rate at age  $x$ .

It was assumed the recovery rate was 5% for ages 60-90 and then graded linearly down to 0% by attained age 95. This was chosen such that disability proportion does not rise too high at older ages. In addition, in this model, incidence rates and mortality followed the additive model alluded to above. In practice, it may be more precise to develop a model that is monthly. Now we can move on to  $W_2$ . Note again, this is the complete formula. No benefit exhaustions were assumed (i.e. we are assuming a lifetime benefit period) in the paper.

$$\text{Let: } W_2(x) = W_2(x-1) + W_1(x-1) * d(x) - W_2(x-1) * q_x^d - W_2(x-1) * \text{rec}(x) - \text{benefit exhaustions}(x)$$

Further, this method is holistically limited because it is not time dependent. If it were, mortality and morbidity improvement would have to be considered. Actuaries may assume both mortality and morbidity decrease over time due to technology, public health, medical expertise and other factors. Further, we would also have to consider durational impacts. It is often assumed a 75-year-old just recently issued displays a different mortality pattern than a 75-year-old that has been in force for say 15 years. This is because the recently issued insured has just been underwritten which leads to bias towards good health in the initial years. On the claim side, it is often the case that early claim durations have higher mortality.

### Mortality curves:

In this analysis we will assume that total mortality is equal to 110% of the IAM table. This is based on the author's belief that LTC *total* mortality may be higher than annuitant mortality. I hold this view because LTC benefits people who will need care in their older age and the choice to purchase LTC may be anti-selective. Further and somewhat relatedly, this could be justified in light of various rate increases that have been implemented for LTC products which may lead to healthier policyholders lapsing their policy.

As for the disabled mortality, I have used an SOA table called the "Pri.H-2012 Female Disabled Retiree". I have scaled up the earlier ages in this table so that the disabled mortality to total mortality is roughly 600% and grades down over time. This table is not intended to be an

accurate portrayal of LTC disabled mortality as this paper's goal is to illuminate how the incidence curve can influence the active mortality curve under the assumption you are solving for  $q_x^a$  in the equation [presented](#) above.

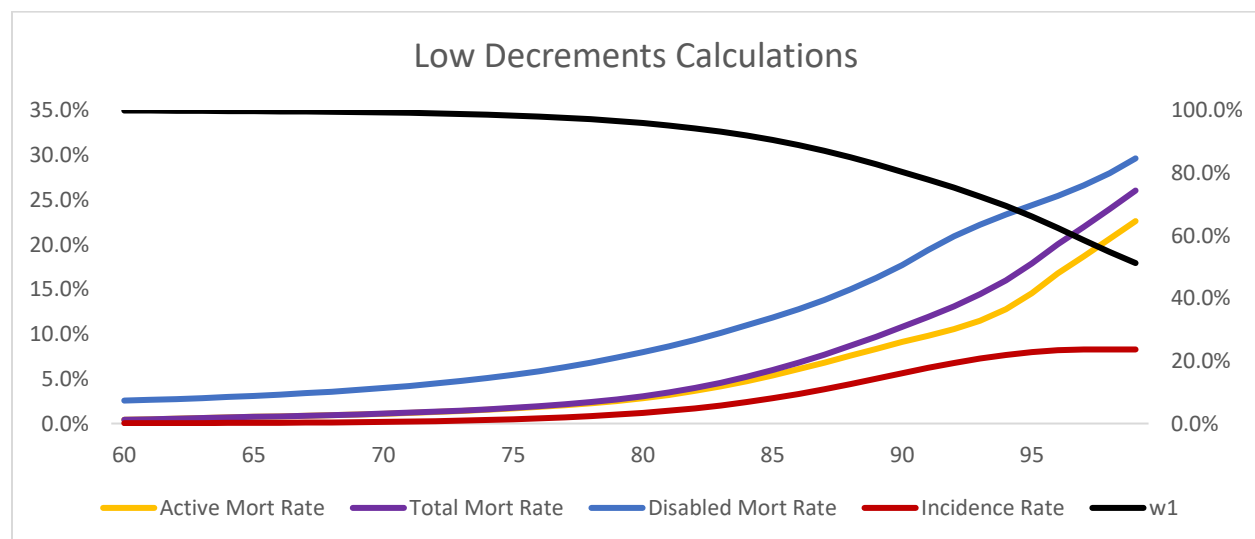
### Incidence Curve:

For the incidence curve I have used a curve from "Model 2" of the "2015 LTC Experience Basic table". Please note that industry data is sparse for LTC given the challenges of conducting an industry LTC experience table.

## **Analysis**

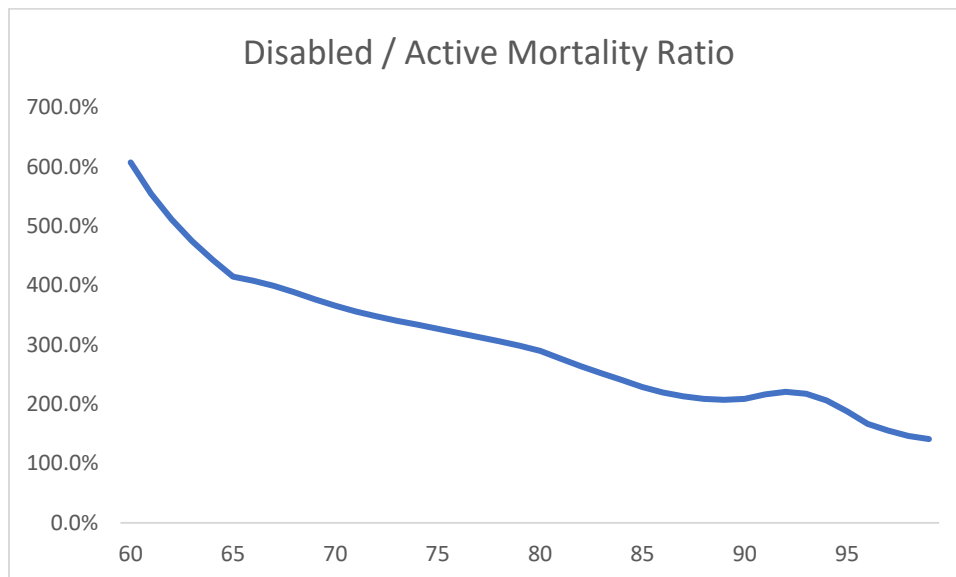
### Baseline Analysis:

Below is the graph of the active, disabled, and total mortality rates. The active mortality rates were solved for, and the disabled and total mortality rates were taken as constants. In addition, the active proportion ( $w_1(x)$ ) is plotted in black. As the age increases, the number of people on claim increases, which conceptually makes sense. This also has an interesting effect on active mortality. The increase in disabled population pulls the active mortality down to compensate for more people being disabled. This effect becomes pronounced beginning at attained age 85 for this set of assumptions. This effect may become less pronounced in older ages if one assumed disabled mortality, active mortality and total mortality must all converge. I have left these older ages out of the graph.



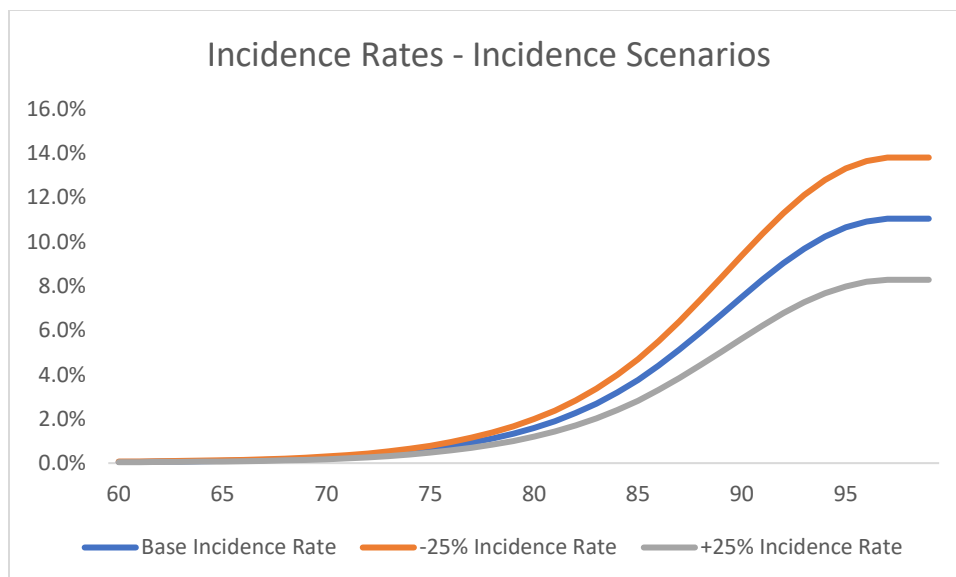
Another thing to consider the ratio of active mortality to disabled mortality. Below is graph of the ratio of disabled mortality to active mortality rates for this set of assumptions. The message from this graph is that disabled mortality and active mortality are significantly different at younger ages. This makes sense since active mortality rates are very low for working-aged people but disabling conditions can be significantly detrimental to health. Further, as people age the mortality goes up and the increase in disabled mortality with age is limited from a relative

standpoint. This is because disabled mortality cannot be above 100%. All of this is to say it seems the health gap of between disabled and active declines with age.



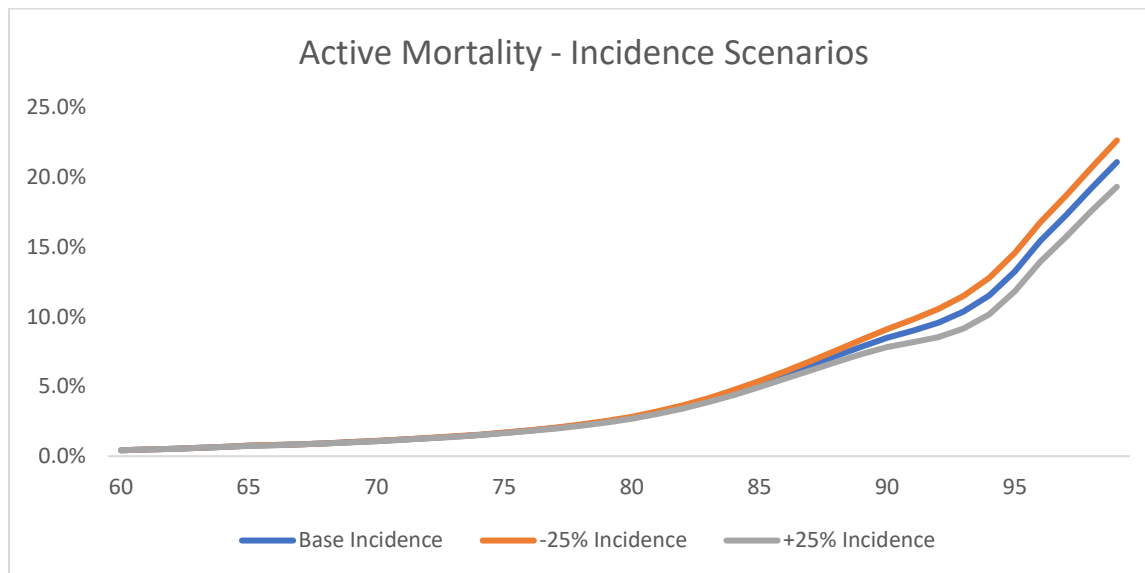
#### Sensitivity testing:

Two scenarios were tested. Incidence increases by 25% and decreases by 25%. Active mortality is solved for, and all other variables remain unchanged. The graph below summarizes the scenario incidence curves when compared to the baseline. Overall, this will directly relate to the proportion of people who are on claim,  $w_2$ .



Now it is time to compare the active mortality for these 3 incidence scenarios. The graph below summarizes the calculated active mortality curves for these three incidence scenarios. It should not be surprising that the baseline scenario is in the middle of the two curves. What may seem counterintuitive is that higher incidence has lower active mortality under this framework. Higher

incidence leads to a higher  $w_2$  which in turn leads to a higher proportion of insureds having mortality rates consistent with the disabled mortality rate. Practically, this means that if an insurance company underestimates incidence and uses the total mortality framework, their error is compounded by lower active mortality (or disabled mortality). However, having higher incidence could be associated with a less healthy population which is why this framework may be conceptually challenging. If this is the case, then perhaps the total mortality curve chosen was also incorrect. Since, total mortality is weighted average of the disabled mortality and active mortality. In this hypothetical scenario, since incidence was higher, that could mean the weighted embedded in the total mortality curve used may have been off as well.



## Conclusions

1. Based on total mortality framework, incidence is linked to active mortality and disabled mortality

We have only assessed the link between active mortality and total mortality by holding disabled mortality constant. As incidence increases, active mortality has to decrease to preserve total mortality. Alternatively, disabled mortality could decrease which seems conceptually possible. With increased incidence, less severe disabilities might be qualifying for LTC benefits and therefore the disabled mortality curve may need to come down to compensate. However, both cases are unfavorable to the insurance company. In the first case, the insurance company's policyholders stay in force for longer since active mortality is lower. Because, LTC is an extremely termination-supported product, the insurance company benefits when the policyholder passes away or stops paying their premiums (in this case at the expense of the policyholder).

Now you may have noticed that I have used the word favorable and clarified those to whom it was favorable. In LTC the insurance company and the insurer's incentives can be unaligned. The policyholder wants to live as long as possible and as healthy as possible. If both conditions are met, then both the insurance company and the policyholder benefit. If the second condition is not met (they go on the claim but stay alive), the insurance company does not benefit. Further, the

historical underpricing of LTC by insurance companies has driven a giant wedge between the insurance company's and the policyholders' incentives. This is because these higher premiums likely spurred healthier policyholders to lapse their LTC policies which leaves less healthy policyholders who may be more likely to need their LTC benefits.

## 2. This paper had limitations and simplifications.

In addition, there are other variables at play here that were criminally simplified for this paper. Recoveries put upwards pressure on active mortality by reducing the proportion of people who are disabled. Benefit exhaustions also put upwards pressure on active mortality by reducing  $w_2$  however, in this case once a person uses up all their benefits, they leave the insurance system and thus the total mortality calculation. Benefit exhaustions are interesting because they cause the average claim duration to decrease. In this paper, it was implicitly assumed that everyone has a lifetime benefit period. Further, there is nuance in that the claim termination rates likely vary by the benefit period type (richer or longer benefit periods have lower claim termination rates). Claim exhaustions also create challenges with using a total mortality curve for LTC since exhaustions censor the data as deaths incurred after benefits run out are not counted. This is likely inconsistent with how the total mortality curve was measured.

Perhaps the most interesting (and complex) variable left out is time. Specifically, it is often assumed that morbidity improves (lowers) with time. This leads to lower incidence over time. In addition, mortality is also assumed to improve with time. In addition, there are the durational effects. For instance, using selection theory from life insurance, it is often assumed a policyholder who was recently underwritten is relatively healthier than a policyholder with the same characteristics but purchased their policy several years ago.

## 3. Is total mortality a valid framework?

This whole exercise relied on assuming the total mortality framework. But what if the total mortality framework itself is not a valid framework for LTC? For example, an insurance company could reduce its incidence assumptions at ages with insufficient data and therefore increase active termination to compensate. They could actuarially justify this argument based on the total mortality framework. However, what if the health of the LTC population is linked to morbidity? Assuming that both morbidity and mortality are positively related to one's health seems like a reasonable assumption (albeit health is difficult to measure). Thus, it appears difficult to develop a total mortality curve because the total mortality curve is influenced by incidence. The LTC insurance population is very niche and therefore may not fit 1-1 to some annuity or life insurance mortality table.

Now the obvious solution would be to measure active mortality on first principles. However, this approach is also limited in that active mortality has become difficult to measure because of a trend known as the underreporting of deaths. Now, at older ages (100+) a total mortality framework may be the most practical method since there likely is little data. Further, the 100+ ages would likely not make a material financial impact on the company since mortality in one's 90s is extremely high and very few people live into their 100s.



Further, another limitation is the total mortality equation in of itself. It is based on incidence, but most life and annuity mortality tables used in practice do not consider for disability status (why would they?). Therefore, in LTC we are trying to find a mortality table that best represents our policies. However, LTC policies have various different product designs (different benefit periods and elimination periods are two examples). Thus, it may be challenging to fit a total mortality curve to one's LTC population. This is less problematic at really older ages due to materiality and the convergence of the various curves. However, for ages such as 85-95 this appears to turn into a leap of faith.

While total mortality is an elegant way to solve for active mortality, it could lead to unintended consequences which can be unforgivable in LTC. LTC is extremely sensitive to, well, just about everything. While disabled mortality may be measured with a fairly good degree of precision, total mortality is most certainly not. It is unlikely that strapping a table onto one's LTC population can truly be representative. At older ages (100+) it may not matter since mortality rates are very high. However, at the ages between 75-94 it seems unwise to choose elegance for the sake of its simplicity. These ages will materially impact the financials of an insurance company as these are prime years when insureds start going on claim. Total mortality, while an interesting concept, may not be appropriate. It appears by following total mortality, we have simply swapped measuring active mortality imprecisely for a moving target in total mortality. Perhaps it would be more conceptually sound to estimate active mortality, and adjust (somehow) for the underreporting of deaths.

## Appendix 1: Mortality Methods

Below there is a table with made up numbers that will be considered the data for an experience study over three years. Notice that there are two decrements active deaths and new claims. Based on this data we can estimate death rates and claim incidence. We will use the additive method first (also called “uniform distribution of deaths”) and next the multiplicative method (in this case assuming a “constant force of mortality”).

| <b>Table 1: Appendix 1 Experience Study</b> |            |                         |                      |               |                  |
|---------------------------------------------|------------|-------------------------|----------------------|---------------|------------------|
| <b>Year</b>                                 | <b>Age</b> | <b>Active Lives BOY</b> | <b>Active Deaths</b> | <b>Claims</b> | <b>Lives EOY</b> |
| 1                                           | 60         | 1000                    | 5                    | 3             | 992              |
| 2                                           | 61         | 992                     | 6                    | 4             | 982              |
| 3                                           | 62         | 982                     | 7                    | 5             | 970              |

Additive method: Uniform Distribution of Deaths.

$$q_x^a = \frac{Deaths(x)}{Lives^{BOY}(x)}; \quad d(x) = \frac{Claims(x)}{Lives^{BOY}(x)}$$

$$\Rightarrow Lives^{EOY}(x) = Lives^{BOY}(x) * (1 - d(x) - q_x^a)$$

Using these equations, we can get to the following death rates.

| <b>Table 2: Appendix 1 Additive Mortality Rate</b> |            |                       |                   |
|----------------------------------------------------|------------|-----------------------|-------------------|
| <b>Year</b>                                        | <b>Age</b> | <b>Mortality Rate</b> | <b>Claim Rate</b> |
| 1                                                  | 60         | 0.500%                | 0.300%            |
| 2                                                  | 61         | 0.605%                | 0.403%            |
| 3                                                  | 62         | 0.713%                | 0.509%            |

Multiplicative method: Assuming constant force of mortality

This method is a little bit more challenging as it requires calculus. It relies on the following equations. I denoted the multiplicative decrements with primes to differentiate from the additive method.

$$Lives^{EOY}(x) = Lives^{BOY}(x) * (1 - d'(x)) * (1 - q'_x{}^a) = Lives^{BOY}(x) * {}_1p_x$$

$$Let \quad {}_1p_x = e^{-(u^q(x) + u^d(x))};$$

where  $u^q(x)$  is the force of mortality and  $u^d(x)$  is the force of incidence

$$\Rightarrow (q'_x{}^a) = 1 - e^{-(u^q(x))}, \Rightarrow d'(x) = 1 - e^{-(u^d(x))}$$

$$\frac{Deaths(x)}{Lives(x)} = \int_0^1 u^q * e^{-(u^q * t + u^d * t)} dt = -u^q * \frac{e^{-(u^q * t + u^d * t)}}{u^q + u^d} \Big|_0^1 = \frac{u^q}{u^q + u^d} * (1 - e^{-(u^q + u^d)})$$

$$\frac{Claims(x)}{Lives(x)} = \int_0^1 u^d * e^{-(u^q * t + u^d * t)} dt = -u^d * \frac{e^{-(u^q * t + u^d * t)}}{u^q + u^d} \Big|_0^1 = \frac{u^d}{u^q + u^d} * (1 - e^{-(u^q + u^d)})$$

$$\Rightarrow \frac{Claims(x)}{Deaths(x)} = \frac{u^d}{u^q} \Rightarrow u^d = \frac{Claims(x)}{Deaths(x)} * u^q = b(x) * u^q$$

$$\Rightarrow {}_1p_x = e^{-(u^q + u^q * b(x))} \Rightarrow -\frac{\ln({}_1p_x)}{1 + b(x)} = u^q = -\frac{\ln({}_1p_x) * Deaths(x)}{Deaths(x) + Claims(x)}$$

$$\Rightarrow u^d = -\frac{\ln({}_1p_x) * Claims(x)}{Deaths(x) + Claims(x)}$$

Below summarizes the force of mortality and force of incidence as well as the conversions to annual mort rate and claim rate. Note that this method is not significantly different than the previous calculation. The methodology used to measure decrements should not adversely impact results so long as the measurement is consistent with how it is implemented in the model.

| <b>Table 3: Appendix 1 Multiplicative Mortality Rate</b> |            |                      |                           |                  |                   |
|----------------------------------------------------------|------------|----------------------|---------------------------|------------------|-------------------|
| <b>Year</b>                                              | <b>Age</b> | <b>Force of Mort</b> | <b>Force of Incidence</b> | <b>Mort Rate</b> | <b>Claim Rate</b> |
| 1                                                        | 60         | 0.502%               | 0.301%                    | 0.501%           | 0.301%            |
| 2                                                        | 61         | 0.608%               | 0.405%                    | 0.606%           | 0.404%            |
| 3                                                        | 62         | 0.717%               | 0.512%                    | 0.715%           | 0.511%            |

Further, I must add caution about the practicality of the force of mortality. Integrating works great in theory. In practice, I would advise against it. Another option would be to adjust the time period to be to convert experience data to calculate it on a monthly basis rather than an instantaneous basis. This can then be implemented by dividing the year into 12 months rather than dividing it into infinitesimal time period with the help of calculus. Further, a simplification may be appropriate where you assume that incidence happens before deaths (or vice versa so long as these rates are measured consistently with the modeling).

## References

- Bluhm, W. F., & Leida, H. (2015). Individual Health Insurance (2nd ed.). ACTEX Publications.
- Brewster, R., & Gutterman, S. (2014). The volatility in long-term care insurance - society of actuaries (SOA). <https://www.soa.org/globalassets/assets/files/research/projects/research-ltc-volatility-report.pdf>
- Eaton, R. & Morton, M. (2022). Insuring Long Term Care. ACTEX.
- HEALTH INSURANCE PORTABILITY AND ACCOUNTABILITY ACT OF 1996 (HIPPA), 110 Stat. 1936, § 325 (1996).  
<https://www.congress.gov/104/plaws/publ191/PLAW104publ191.pdf>
- Matthews, F. E., Arthur, A., Barnes, L. E., Bond, J., Jagger, C., Robinson, L., & Brayne, C. (2013). A two-decade comparison of prevalence of dementia in individuals aged 65 years and older from three geographical areas of England: results of the Cognitive Function and Ageing Study I and II. *The Lancet*, 382(9902), 1405-1412.
- Rose, G. (2023). *Government acknowledges major issues with Death master file*. Lewis & Ellis Inc. <https://lewisellis.com/industry-insights/article/561281-government-acknowledges-major-issues-with-death-master-file>
- Simon, G. (n.d.). The earliest life insurance policy.  
<https://pages.stern.nyu.edu/~gsimon/InsuranceHistoryPage/FirstLifePolicy.pdf>
- Society of Actuaries. (n.d.). Mortality and other rate tables. <https://mort.soa.org/>