**Scenario Generator User’s Guide**

Overview

The representative scenarios method for reserve calculation requires representative scenarios for each major risk. A small number of such scenarios are desired, and they are representative in the sense that they correspond to specified percentile levels in the distribution of all stochastic scenarios for that risk.

This User’s Guide is organized into the following sections:

1. Contents of a scenario, and how the information in the scenario is intended to be used.
2. The input that a user must provide to the generator before creating a set of scenarios.
	1. Define the set of scenarios to be generated
	2. Define the initial economic conditions
	3. Define the list of risks and their distributions
3. How a scenario is generated, including the role played by the user’s input.
	1. Generating a scenario path for one risk
	2. Combining risks in a scenario and sets of scenarios
	3. Assigning weights to scenario paths and scenarios

The following appendices address some more technical details:

To do: Draft the appendices

* Appendix 1: A sample specification of all user input to the generator
* Appendix 2: The software interface used to access scenario data in a model
* Appendix 3: Calculating the reserve (To do: decide if this belongs in this document or a different one)
	+ Calculating the present value of cash flows from each scenario
	+ Weighting scenarios to obtain the anticipated experience reserve
	+ Calculating the aggregate margin

1. Contents of a scenario

A scenario contains month-by-month information to be used in a model that simulates the financial results of a block of business in an insurance company. The scenario information for any one month includes both economic conditions and experience levels (e.g. adjustments to expected experience).

The information for each month of each scenario must span all of the risks that are to be simulated using representative scenarios. A sample list of risks and the corresponding scenario information is provided below:

|  |  |
| --- | --- |
| Risk | Scenario information for each month |
| Interest rate risk | Yield curve for government bonds |
| Credit risk | Yield spreads and default rates by credit rating |
| Equity investment price risk | Returns for each type of investment or equity index |
| Expense inflation risk | Inflation rate |
| Mortality risk | Adjustments to tabular mortality rates (see discussion below) |
| Lapse rate risk | Adjustments to tabular lapse rates (see discussion below) |
| GLIB election risk | Adjustments to tabular GLIB election rates (see discussion below) |

Scenario adjustments to tabular decrement rates can take two forms: an additive adjustment and/or a multiplicative adjustment. A model uses these adjustments in the following way to calculate the simulated experience decrement rate for a month:

*Simulated experience rate = [(Tabular rate) x (multiplicative adjustment)] + (additive adjustment)*

Typically, the tabular rate will come from a table with values that vary by age of insured, contract duration, or other parameters. The adjustments for a particular risk (e.g. mortality) are applied across the board to every value in the corresponding table, possibly subject to a maximum or minimum adjusted value.

The reason for allowing both additive and multiplicative adjustments is that when the adjustments are to be applied to a range of values sometimes one or the other type of adjustment is most appropriate. For example, a multiplicative adjustment will have no effect on tabular values of zero, so an additive form of adjustment might be more appropriate for tables that contain zeroes.

Scenario values for information other than adjustments to actuarial decrements such as mortality rates or lapse rates come from specialized generator formulas developed specifically for each risk. For example, interest rates and equity returns are generated using the formulas in the economic scenario generator adopted for VM-20. In the case of GLIB election risk, the generator provides a “sensitivity factor” that can be used to adjust tabular election rates based on the degree of in-the-moneyness. The adjustment of the tabular election rates based on the sensitivity factor is complex and must be built into the simulation model. (To do: explain how this adjustment is done)

The list of risks for which scenario data is generated can vary from product to product when using the representative scenarios method. Certain risks, mainly investment risks, are always included in the list by default. The user must provide input to the scenario generator to specify the additional risks to be simulated and the scenarios to be generated. This user input is discussed in the next section.

2. User input required to define scenarios

2.1 Define the set of scenarios to be generated

While the scenario generator was created to provide scenario sets for the representative scenarios method, the generator can also provide two other kinds of scenario sets. The user must specify which of the following three kinds of output is desired.

* **Representative scenarios.** A small number of scenarios is generated for each risk, each at a specified percentile level in the distribution for the risk. In each percentile level scenario, the values for all risks other than the one being shocked are at the anticipated (median) level. The total number of scenarios is the sum of the number of scenarios for each risk[[1]](#footnote-1).
* **Grid of representative scenarios.** A small number of scenarios is generated for each risk, each at a specified percentile level in the distribution for that risk. But then risks are combined within scenarios so that the scenario set includes a scenario for every combination of percentile levels across risks. The total number of scenarios is the product of the number of percentile level scenarios for each risk. For example, if there are four risks and five percentile level scenarios for each risk, the total number of scenarios is 5 x 5 x 5 x 5 = 625.
* **Stochastic scenarios.** A large number of scenarios is generated using random shocks for each risk in each month. The user must specify the number of scenarios to be generated.

2.2 Define the initial economic conditions

The conditions at the beginning of each scenario must be the same, and the user must specify what they are. Therefore the user must specify the following:

* The date from which scenarios start. Since these scenarios are used for valuation, this date can be called the valuation date.
* The risk-free yield curve (for US treasuries) on the valuation date.
* To do: decide whether initial credit spreads and default rate levels need to be specified.

2.3 Define the list of risks and their distributions

The user must define the list of risks to be simulated. Certain risks (e.g. investment risks) are always simulated by default, so the user only needs to specify the additional risks associated with the product for which reserves are to be calculated. The risks that are always simulated by default are:

* Interest rate risk
* Equity investment price risk
* Expense inflation risk
* To do: decide how credit risk (yield spreads and default rates) will be dealt with. Perhaps we could use the work of the Academy C-1 Work Group and the NAIC Investment RBC Working Group to guide us here.

Typically, the remaining risks that must be specified by the user are associated with actuarial decrements such as mortality rates or lapse rates. For each such decrement that represents a major risk, the user must specify the risk and the type of adjustment factors and must specify certain percentile points on the distribution for each adjustment factor. In particular, the values of each adjustment factor must be specified at the following percentile points:

0.1% (-3 standard deviations)

16% (-1 standard deviations)

50% median

84% (+1 standard deviation)

99.9% (+3 standard deviations)

These percentile points correspond to the distribution for an actuarial risk such as mortality rates or lapse rates rate over a period of one year[[2]](#footnote-2). When specifying these percentile points, one can use a technique developed for use in actuarial experience studies. In evaluating observed decrement rates, an actuary needs to evaluate the likelihood that the rate observed from a limited sample is a statistical fluke or outlier and not representative of the true underlying decrement rate. This can be done by estimating the range within which the true rate must fall with a given level of certainty, based on the observed data.

Methods for estimating this range differ depending on whether the experience study provides only raw experience decrement rates or whether the study provides a ratio to some expected experience rate (Actual / Expected or A/E ratio). The next two subsections discuss each case separately.

2.3.1 When the experience study produces only raw decrement rates

Sometimes an experience study provides only a count of policies exposed to risk and a count of observed decrement events[[3]](#footnote-3). For example, studies of lapse rates are often reported in this manner.

Confidence bounds with a desired probability level within which the true lapse rate (or other decrement rate) falls can be constructed using simple formulas based on the observed number of policies exposed and the observed number of lapses. Generally, the observed number of lapses is not very small so the binomial distribution can be used as a basis for computing the confidence bounds.

The following formulas can be used to calculate confidence bounds for the lapse rate[[4]](#footnote-4):

Lower Bound =

Upper Bound =

where:

Z = width of the confidence interval in units of 1 standard deviation. For a 95% confidence interval, Z = 1.96. For a (1-α) confidence interval, Z is the value of the inverse normal distribution function at 1-(α/2).

The same formulas can be used for decrements other than lapse rates by using the number of observed decrements and the observed decrement rate in place of the number of lapses and lapse rate.

Suppose an insurer has established a table of lapse rates by issue age, duration and product. (For example, an issue age, duration, product may have 500 lapses and has 10,000 policies exposed in a calendar year resulting in a lapse rate of 0.05.) Using the formulas above, a 95% confidence interval for the lapse rate is from 0.046 to 0.054. Therefore, we can say with 95% confidence that the true lapse rate falls within this interval.

The values required by the generator can also be calculated for this example. First let’s calculate the values for the aggregate observed lapse rate at the five percentile levels that are required:

0.1% Value is lower bound with Z = 3 Lapse rate = 0.0435

16% Value is lower bound with Z = 1 Lapse rate = 0.0478

50% Value is the observed lapse rate Lapse rate = 0.0500

84% Value is upper bound with Z = 1 Lapse rate = 0.0522

99.9% Value is upper bound with Z = 3 Lapse rate = 0.0565

The generator requires adjustment factors that can be applied to a tabular lapse rate. If we wish for multiplicative adjustment factors, we can calculate them as follows:

0.1% Multiplicative adjustment factor is 0.0435 / 0.0500 = 0.870

16% Multiplicative adjustment factor is 0.0478 / 0.0500 = 0.956

50% Multiplicative adjustment factor is 0.0500 / 0.0500 = 1.000

84% Multiplicative adjustment factor is 0.0522 / 0.0500 = 1.044

99.9% Multiplicative adjustment factor is 0.0565 / 0.0500 = 1.130

If we wish for additive adjustment factors, we can calculate them as follows:

0.1% Additive adjustment factor is 0.0435 - 0.0500 = -0.0065

16% Additive adjustment factor is 0.0478 - 0.0500 = -0.0022

50% Additive adjustment factor is 0.0500 - 0.0500 = 0.0000

84% Additive adjustment factor is 0.0522 - 0.0500 = +0.0022

99.9% Additive adjustment factor is 0.0565 - 0.0500 = +0.0065

One can use either or both of multiplicative and additive adjustment factors, but double counting must be avoided. If both adjustment factors are used, then each must be reduced (e.g. use 60% of the multiplicative adjustment factor and 40% of the additive adjustment factor derived above).

The choice of whether to use multiplicative or additive forms of adjustments depends on the nature of the decrement being adjusted. The actuary must use judgment in deciding how these adjustments can most realistically be applied in the model.

2.3.2 When the experience study provides an Actual / Expected ratio

Sometimes an experience study involves comparing the actual number of observed events (e.g. deaths) to an expected number. The actual and expected numbers are compared by calculating an Actual to Expected (A/E) ratio. If the A/E ratio is 1.0 then one has evidence that the mortality experience is consistent with the expected basis mortality , and if the A/E ratio is much different from 1.0 then there is evidence that the mortality experience is something other than the expected basis mortality. One can evaluate the strength of that evidence by determining a confidence interval around the observed A/E ratio. The confidence interval can be calibrated to any desired probability level, that is, to any desired probability that the true A/E ratio falls inside the interval.

For example, suppose an insurer studies a block of life insurance contracts and observes 525 deaths during a calendar year. Based on its pricing mortality table, only 500 deaths were expected. The A/E ratio is 1.05.

The following formulas can be used to calculate a confidence interval around the A/E ratio[[5]](#footnote-5).

Lower bound = Upper bound =

where:

A = actual deaths

E = expected deaths

Z = width of the confidence interval in units of 1 standard deviation. For a 95% confidence interval, Z = 1.96. For a (1-α) confidence interval, Z is the value of the inverse normal distribution function at 1-(α/2).

Using our sample data with an observed A/E ratio of 1.05, we find that a 95% confidence interval for the A/E ratio is from 0.96 to 1.14. Since 1.05 falls inside that interval, we cannot say with 95% confidence that the mortality experience is something other than the expected basis mortality.

The values required by the generator can also be calculated for this example. Let’s assume we wish to define a multiplicative adjustment factor. Values for that adjustment factor must be specified for the following percentiles:

0.1% Value is lower bound with Z = 3 Value = 0.918

16% Value is lower bound with Z = 1 Value = 1.004

50% Value is the A/E ratio Value = 1.050

84% Value is upper bound with Z = 1 Value = 1.098

99.9% Value is upper bound with Z = 3 Value = 1.195

2.3.3 A note on the level of experience aggregation

The experience study should be at a level of aggregation corresponding to the block of business for which reserves are being calculated. Normally, decrement rates will come from a table with values that vary by age or other criteria. All values in the tables will be adjusted using the same adjustment factors when scenarios are run through the simulation model. Therefore, the number of claims or other decrement events used in the formulas above can be the total for the full block of business rather than the much smaller subtotals for subgroups by age or other criteria.

2.3.4 A note on dynamically linked assumptions

Sometimes a model will dynamically link one assumption to another. For example, lapse rates on fixed annuities may increase when external market interest rates exceed the rate being credited on the contract. The model may set the experience lapse rate equal to a tabular lapse rate plus an adjustment that is a function of interest rates. The adjustments being discussed here are not a replacement for this dynamic behavior. Rather, these adjustments are to be applied in addition to that dynamic behavior. Recall the formula shown earlier:

*Simulated experience rate = [(Tabular rate) x (multiplicative adjustment)] + (additive adjustment)*

In this formula, the “tabular rate” is the dynamically adjusted tabular rate. The multiplicative and/or additive adjustments are applied after the dynamic adjustment.

This is important because in some cases, notably lapse rates for some products, the dynamic adjustments create more variability in simulated experience than the statistical variation simulated by the adjustments being discussed here.

3. How a scenario is generated

A separate document titled “Development of Scenarios for the Modeled Reserve”, discusses the analogy between a scenario path for one risk and a random walk. In this section we will review how a representative scenario path for an actuarial decrement risk (mortality) is generated, and then discuss how all risks are combined in sets of scenarios.

3.1 Generating a scenario path for one risk

The following items are needed to generate a scenario path for one risk:

1. A selected path for this representative scenario (e.g. pop-up or 20-year creep-up)
2. A selected percentile level for this representative scenario
3. The list of adjustment factors that simulate changes from anticipated experience for this risk.
4. For each adjustment factor, the value at each of five percentile points on its distribution (0.1%, 16%, 50%, 84%, 99.9%)

As an example, let’s say that the risk is mortality, the selected percentile level is 99.9% (very adverse) and the selected path is pop-up.

Next, we need the list of adjustment factors. For mortality let’s assume we have two adjustment factors:

* A multiplicative adjustment to the mortality rate
* A multiplicative adjustment to the mortality improvement scale

The scenario consists of a value for each adjustment factor in each calendar month. We will calculate the monthly values for each of the two adjustment factors in turn.

Note that the adjustment factors will be the same for each month within a year and will change on a yearly basis. This reflects the fact that the distribution for each adjustment factor is defined based on variability for an annual time period. The adjustment factor for a year is calculated and then used for 12 consecutive months in the scenario path.

The multiplicative adjustment for mortality for each year is based on the pattern of representative shocks in the 99.9% pop-up random walk[[6]](#footnote-6). Those shocks change on an annual basis; the first few values are:

Year 1 3.000

Year 2 1.243

Year 3 0.954

Year 4 0.804

These figures are shocks measured in standard deviations. In an earlier example, we derived the distribution for a multiplicative adjustment for mortality, so let’s use that distribution. Values were:

99.9% (3 standard errors) 1.195

84% (1 standard error) 1.098

50% (0 standard error) 1.050

16% (-1 standard error) 1.004

0.1% (-3 standard errors) 0.918

The monthly values for the multiplicative adjustment are interpolated from this distribution. The first 12 months correspond to the year 1 shock of 3 standard deviations, so they are all equal to 1.195. The second 12 months correspond to the year 2 shock of 1.243 standard deviations, so they are equal to the interpolated value of 1.10 (which is interpolated between 1.195 and 1.098). Continuing in this fashion, one can compute the multiplicative adjustment factor for the mortality rate for each future month.

The other adjustment – the multiplicative adjustment to the mortality improvement scale – is calculated differently because its distribution is defined differently. Mortality improvement is a special case because the distribution is defined not for a single year but for the entire future. The adjustment factor does not change over time so it has the same value every month. The value does not depend on the scenario path (pop-up or creep-up); it depends only on the scenario percentile level. The adjustment factor for every month is equal to the value at the scenario percentile level in its distribution.

Suppose the distribution for the multiplicative adjustment to the mortality improvement scale were defined by the user as follows[[7]](#footnote-7):

99.9% (3 standard errors) 2.00 (e.g. double the rate of improvement in the improvement scale)

84% (1 standard error) 1.20

50% (0 standard error) 1.00 (e.g. no change to the scale)

16% (-1 standard error) 0.80

0.1% (-3 standard errors) 0.10

We wish for a scenario at 99.9% (3 standard errors) so the value from this distribution is 2.00 and is the same for every month.

Note that these values for both adjustment factors appear in the same scenario for this risk. While mortality risk may have two aspects (statistical variability and rate of improvement), we are treating them both together as one risk, not two separate risks.

Note that the anticipated experience scenario for mortality must also specify values for each of these adjustment factors. Based on the user’s input of the distributions of these adjustments, the anticipated experience scenario has values of 1.05 for the adjustment to the mortality rate and 1.00 for the adjustment to the mortality improvement scale. Both of these values are the same for every month in the anticipated experience scenario.

3.2 Combining risks in a scenario and sets of scenarios

The way risks are combined in a scenario depends on the kind of scenario set that is requested. There are three kinds of scenario sets.

3.2.1 Representative scenarios

A set of representative scenarios for all risks combined starts from the sets of representative scenario paths for each risk. A representative scenario for all risks combined contains one scenario path for each risk, and all risks except one follow their anticipated path.

That is to say, all of the representative scenarios for mortality risk include anticipated experience for all other risks including interest rates, lapse rates, etc. All of the representative scenarios for interest rate risk include anticipated experience for mortality, lapse rates, and so on.

Suppose one has identified four risks, and one has representative scenario paths for each risk at the following percentile levels:

99.9% pop-up

84% pop-up

50% anticipated

16% pop-down

0.1% pop-down

One therefore has four risks and a total of 4 x 5 = 20 scenario paths. However, there are just 17 representative scenarios. These are:

Scenario 1: Anticipated path for all four risks

Scenarios 2-5: Anticipated paths for risks 2, 3, and 4, the four other paths for risk 1

Scenarios 6-9: Anticipated paths for risks 1, 3, and 4, the four other paths for risk 2

Scenarios 10-13: Anticipated paths for risks 1, 2, and 4, the four other paths for risk 3

Scenarios 14-17: Anticipated paths for risks 1, 2, and 3, the four other paths for risk 4

Note that when other risk variables are dynamically linked to one particular risk such as interest rates, then the model results for representative scenarios for the linked risk (e.g. interest rates) include the effect of that dynamic link. The link occurs inside the model, and is not part of the scenario data itself. For example, if lapse rates are dynamically linked to interest rates, a representative scenario defined as focusing on interest rate risk will include anticipated (or median) lapse rates in the scenario definition. However, within the simulation model lapse rates will be adjusted according to the dynamic link to interest rates in the scenario. The dynamic behavior of lapse rates will therefore be quantified as part of the measure of interest rate risk and not as part of lapse rate risk.

3.2.2 Grid of representative scenarios

To make a grid of representative scenarios, we again start with the set of representative scenario paths for each risk. To generate a scenario for all risks combined, we take one scenario path for each risk and put them together. The term “grid” comes from the idea that a grid of representative scenarios includes all permutations and combinations that can be created by picking one scenario path for each risk and combining them into a scenario for all risks combined.

If there are four risks and five paths for each risk, then the number of scenarios in the grid is 54 = 625.

 3.2.3 Stochastic scenarios

In a stochastic scenario, each month’s values are generated using a random shock for each risk. The random shocks come from a random number generator seeded with a value based on the scenario number; they are not the formulaic random shocks used for the representative scenarios. The random shocks for each risk are uncorrelated with one another. There is no attempt to make any single scenario representative of a percentile level for any risk. As a result, a large number of scenarios must be generated in order to get a good picture of the distribution of results.

3.3 Assigning weights to scenario paths and scenarios

One must assign a probability weight to each scenario in a set of scenarios so that the results of each scenario can be weighted together to approximate the “mean”. In the representative scenarios method, the reserve is the sum of this “mean” and a “margin” that is based on variations from the mean.

To calculate the weight for a representative scenario or for each scenario in grid, we need the following:

 Weight assigned to risk r. The sum of these weights must equal 1.0

 Probability weight for scenario path s for risk r. The sum of these probability weights for risk r must equal 1.0 for each risk r.

Across all risks r:

Separately for each risk r:

The weights assigned to each risk may be subjective. No standard approach has been developed to assign these weights. For the field test we will use equal weights[[8]](#footnote-8).

The probabilities assigned to each scenario path will be defined as follows.

Each scenario path corresponds to a specific percentile level in the cumulative distribution of the risk variable. Call that percentile level . Using the inverse normal distribution function, we can determine the number of standard errors from the mean corresponding to and call it .

We will set the weight for scenario s equal to the total probability under the normal bell-shaped curve from x-axis point to . This probability is easily calculated using the cumulative normal distribution function.

For the outlier scenarios where either or does not exist, the corresponding value of is the limiting value of either 1 or 0.

Here is a table illustrating the calculation of these weights:

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  |  |  |  | Weight |
|  |  | +infinite | 1.000 |  |
| 99.9% | 3 |  |  | 0.023 |
|  |  | 2 | 0.977 |  |
| 84.1% | 1 |  |  | 0.286 |
|  |  | 0.5 | 0.691 |  |
| 50.0% | 0 |  |  | 0.383 |
|  |  | -0.5 | 0.309 |  |
| 15.9% | -1 |  |  | 0.286 |
|  |  | -2 | 0.023 |  |
| 0.1% | -3 |  |  | 0.023 |
|  |  | -infinite | 0.000 |  |
|  |  |  |  |  |

The figure below illustrates the concept used for these weights. The normal bell-shaped curve is evident, and there are vertical black lines rising from the points on the x-axis where there are data points to be weighted, that is, at 3, 1, 0, -1, and -3. There is shading under sections of the curve. The area of the shaded sections corresponds to the probability weights. The shaded area around each data point (vertical black line) corresponds to the weight given to the corresponding data point. For example, the green shaded area between x-axis points 0.5 and -0.5 corresponds to the weight given to the data point at 0. The purple shaded area between 2.0 and 0.5 corresponds to the weight given to the data point at 1.0.

Note that while the normal curve is used as the basis for the weights applied to the data points, the data values themselves may be skewed. Because of this, it is not likely that the weighted average of the data points will equal the median of the distribution. This means that the mean reserve (before margin) will not equal the present value of cash flows in the anticipated experience (50th percentile) scenario.

In some cases, there may be more than one scenario that corresponds to a given percentile level. For example, there may be both a “pop-up” and a “creep-up” scenario at the same percentile level. In this situation, the weight for that percentile level is divided equally between the scenarios at that percentile level.

With the weights for each scenario path within a risk determined, we can proceed to specifying the weights to be applied to scenarios that combine multiple risks.

3.3.1 Weights for representative scenarios

The weights for a representative scenario (not in a grid), other than the anticipated path for all risks, is the following, where risk r is the one risk not following its anticipated path in this scenario:

In this formula, corresponds to the scenario path weight for the path of risk r in this scenario.

The weight for the anticipated experience scenario in a set of representative scenarios is the remainder after subtracting from 1.0 the weights of all the other scenarios. Or, more directly,

3.3.2 Weights for scenarios in a grid

The weight for each scenario in a grid of representative scenarios is the following:

where corresponds to the path weight for the scenario path of risk r in this scenario.

3.3.3 Weights for stochastic scenarios

In the case of stochastic scenarios the probability weight of each scenario is the same. If there are N scenarios, the weight for each scenario is 1/N.

1. Actually, the total number of unique scenarios will be slightly smaller because only one scenario with all risks at the anticipated level is required. [↑](#footnote-ref-1)
2. While the percentile points for decrement rates correspond to the distribution of a decrement rate over one year, in cases where mortality improvement is included as part of the mortality risk, it is treated differently. The distribution for mortality improvement corresponds to the distribution over all future time. Typically the adjustment for mortality improvement will be a multiplicative adjustment to a tabular mortality improvement scale. The user must provide values of that multiplicative adjustment factor at various percentile levels in its distribution. When a scenario is generated for mortality at a specified percentile level, the multiplicative adjustment factor for mortality improvement will have the same value in every month in the scenario. [↑](#footnote-ref-2)
3. Sometimes studies are carried out by amount of insurance rather than by policy count. For purposes of developing statistical confidence bounds, however, it is much more straightforward to work with policy counts. [↑](#footnote-ref-3)
4. These formulas are based on the binomial distribution and are appropriate when the observed number of decrements is reasonably large (e.g. over 35). [↑](#footnote-ref-4)
5. These formulas are based on the Poisson distribution which can be more appropriate when the number of actual deaths (or other decrements) is small. [↑](#footnote-ref-5)
6. The pattern of these shocks was described in “Development of Scenarios for the Modeled Reserve” [↑](#footnote-ref-6)
7. Since so much judgment is required when setting this distribution, regulators may decide to specify the values to be used. [↑](#footnote-ref-7)
8. Other approaches might assign greater weight to risks that exhibit greater variability between scenario path results, or to risks whose distribution of scenario path results appears most skewed. [↑](#footnote-ref-8)