Abstract

The Myers and Read capital allocation formula is an important new actuarial result. In this paper, we give an overview of the Myers and Read result, explain its significance to actuaries, and provide a simple proof. Then we explain the assumption the allocation formula makes on the underlying families of loss distributions as expected losses by-line vary. Finally we show that this assumption does not hold when insurers grow by writing more risks from a discrete group of insureds—as is typically the case. This failure will severely limit the practical application of the allocation formula.

1 Introduction

In an important paper for actuaries, Myers and Read (2001) showed how to allocate the expected policy holder deficit in a multi-line insurance company uniquely to each line. Their work can also be used to allocate surplus to each line. Previous work on the allocation problem, including Phillips et al. (1998) and Merton and Perold (2001), had concluded that such an allocation could be inappropriate and misleading. The Myers and Read result is, therefore, a significant breakthrough, with obvious importance to actuaries.
Myers and Read repeatedly stress their result is independent of the distribution of losses by line and of any correlations between lines that may exist. They say their “proof requires no assumptions about the joint probability distributions of line-by-line losses and returns on the firm’s portfolio of assets.” However, while their result makes no assumptions about the static distribution of losses with fixed expected loss by line, their derivation does make an important assumption about how the dynamic distribution of losses changes shape with changing expected losses by line. This paper will explain the significance of the latter assumption. We will show it is a necessary and sufficient condition for the Myers and Read result to hold. Most importantly, we will show that the assumption does not hold when insurers grow through the assumption of risk from discrete insureds—as is typically the case.

For the convenience of readers not familiar with Myers and Read’s work, we begin with an overview. Consider a simple insurance company which writes two lines of business. The losses from each line are represented by a random variables $X_1$ and $X_2$, with means $x_1$ and $x_2$. Since the company can choose to write more or less of each line, we assume that the families $X_1(x_1)$ and $X_2(x_2)$, with varying means $x_1$ and $x_2$, are specified. For example, losses from line 1 may be normally distributed with mean $x_1$ and standard deviation 1000 and for line 2 be normally distributed with mean $x_2$ and coefficient of variation $\nu$. Assume the company has capital $k$ and total assets $x_1 + x_2 + k$. Also assume that interest rates are zero. (Myers and Read show how to convert from deterministic investment income to
stochastic income. We focus on deterministic income and set it equal to zero for simplicity. Nothing of substance is lost in doing so.) Let

\[ I(x_1, x_2, k) = \Pr(X_1 + X_2 > x_1 + x_2 + k) \]

be the probability of insolvency. Finally, assume that the company holds its probability of insolvency constant, by adjusting writings of each line and the amount of capital held. Let \( K(x_1, x_2) \) satisfy

\[ I(x_1, x_2, K(x_1, x_2)) = \text{constant}. \]

Then, under certain assumptions on the families \( X_1(x_1) \) and \( X_2(x_2) \) for varying \( x_1, x_2 \), but under no assumptions on the distributions of losses given fixed \( x_1 \) and \( x_2 \) we can prove

\[ x_1 \frac{\partial K}{\partial x_1} + x_2 \frac{\partial K}{\partial x_2} = K. \] (1)

This is obviously a very useful result: it tells the company that it should allocate capital at the rate \( \partial K/\partial x_1 \) to line 1 and \( \partial K/\partial x_2 \) to line 2, and that if it does so the total capital allocation will add up to actual capital! We prove Equation (1) in Corollary 2, below. It is very similar to the actual Myers and Read result, which we prove in Corollary 1.

The main result of the paper, Proposition 1, states the assumptions on the families \( X_i(x_i) \) required for Equation (1) to hold. We show that in most real-world situations these assumptions will, unfortunately, fail to hold. We also give a straight-forward proof of the Myers and Read “adds-up” result and we prove two related extensions. Finally we give several examples to illustrate the results.
The necessary distributional assumption highlights the difference between a continuous “representative insurer” approach, where each insurer assumes a share of a total market risk, and a discrete approach, where insurers assume risk from distinct and discrete individual insureds. The Myers and Read result requires a continuous view as we show in Proposition 1. Examples 4.4 and 4.5 show the result is not true in a discrete environment. Butsic (1999) used the representative insurer argument in his application of Myers and Read.

The rest of the paper is laid out as follows. In the next section we prove two technical lemmas. Section 3 states and proves the main Proposition. Section 4 gives several examples using the main result.

2 Two Technical Lemmas

**Lemma 1** Let \( f : \mathbb{R}^n \to \mathbb{R} \) be a differentiable function of \( n \) variables. Then

\[
x_1 \frac{\partial f}{\partial x_1} + x_2 \frac{\partial f}{\partial x_2} + \cdots + x_n \frac{\partial f}{\partial x_n} = 0
\]

if and only if \( f \) is constant along lines through the origin.

Note: If \( f \) is constant on lines through the origin then \( f \) is called homogeneous. This means that for each \( j \), \( f \) can be expressed as a function of \( x_i/x_j, i = 1, \ldots, n \) when \( x_j \neq 0 \).

**Proof** Sufficiency: if \( f \) is constant along lines through the origin, then by the note we can assume \( f(x_1, \ldots, x_n) = \tilde{f}(x_1/x_n, \ldots, x_{n-1}/x_n) \) for some function \( \tilde{f} \) of \( n - 1 \) variables. An easy calculation shows

\[
x_1 \frac{\partial f}{\partial x_1} + \cdots + x_n \frac{\partial f}{\partial x_n} = \frac{x_1}{x_n} \tilde{f}_1 + \cdots + \frac{x_{n-1}}{x_n} \tilde{f}_{n-1} - x_n \left( \frac{x_1}{x_n^2} \tilde{f}_1 + \cdots + \frac{x_{n-1}}{x_n^2} \tilde{f}_{n-1} \right)
\]

\[= 0,
\]
where \( \tilde{f}_i = \partial \tilde{f}(x_1, \ldots, x_{n-1})/\partial x_i \).

Necessity: Let \( v = (x_1, \ldots, x_n) \) be a differentiable curve, so \( v = v(t) : \mathbb{R} \to \mathbb{R}^n \), with \( dv/dt = v \). This means \( v \) is equal to its own tangent vector for each \( t \).

By separating variables it is easy to see that \( v \) is a line through the origin. (It has the form \( e^t(k_1, \ldots, k_n) \) for constants of integration \( k_i \).) Then, by the chain-rule

\[
\frac{d}{dt} f(v(t)) = x_1 \frac{\partial f}{\partial x_1} + \cdots + x_n \frac{\partial f}{\partial x_n}
\]

\[
= 0,
\]

by assumption, so the directional derivative of \( f \) along any such line \( v \) is constant, i.e. \( f \) is constant along lines through the origin, as required. \( \square \)

**Lemma 2** Let \( f : \mathbb{R}^n \to \mathbb{R} \) be a differentiable function of \( n \) variables. Then,

\[
\sum_{i=1}^{n} x_i \frac{\partial f}{\partial x_i} = f
\]

if and only if there exists a differentiable function \( \tilde{f} \) so that \( f(x_1, \ldots, x_n) = x_1 \tilde{f}(x_2/x_1, \ldots, x_n/x_1) \) for \( x_1 \neq 0 \) and similarly for \( x_2, \ldots, x_n \).

**Proof** If \( f(x_1, \ldots, x_n) = x_1 \tilde{f}(x_2/x_1, \ldots, x_n/x_1) \) then, using subscripts on \( \tilde{f} \) to denote partial derivatives,

\[
\sum_{i=1}^{n} x_i \frac{\partial f}{\partial x_i} = x_1 \tilde{f} - \frac{1}{x_1} \sum_{j=2}^{n} x_j \tilde{f}_{j-1} + \sum_{j=2}^{n} \frac{x_j}{x_1} \tilde{f}_{j-1}
\]

\[
= f.
\]

The first sum comes from the partial derivative with respect to \( x_1 \) and the second sum comes from all the remaining partials.
On the other hand, suppose \( f \) satisfies Equation (3) and let \( \tilde{f}(x_1, s_2, \ldots, s_n) = f(x_1, s_2 x_1, \ldots, s_n x_1) / x_1 \) where \( x_1 \neq 0 \). We must show \( \tilde{f} \) is independent of \( x_1 \). Differentiating

\[
\frac{\partial}{\partial x_1} \left( \frac{f(x_1, s_2 x_1, \ldots, s_n x_1)}{x_1} \right) = -\frac{1}{x_1^2} f + \frac{1}{x_1} \left( \frac{\partial f}{\partial x_1} + \sum_{j=2}^{n} s_j \frac{\partial f}{\partial x_j} \right) = 0
\]

and the result follows. \( \square \)

3 Statement and Proof of Main Result

Before stating the proposition we need to define some more notation. We are modeling a multi-line insurance company. Losses from each line are modeled by random variables \( X_i, i = 1, \ldots, n \), where \( X_i \) has mean \( x_i \) and distribution function \( F_i \). We often regard \( x_i \) as a variable (but not a random variable), so each \( X_i \) is really a family of distributions indexed by \( x_i \). Where necessary we emphasize this by writing \( X_i(x_i) \). Changes in \( x_i \) correspond to increasing or decreasing volume in line \( i \), since \( x_i \) is the a priori expected loss.

Assume that the company holds total assets equal to \( x_1 + \cdots + x_n + k \), so in a very simplistic sense, \( k \) is the capital or surplus of the company.

Next, define the probability of insolvency function and the expected policy-holder deficit function for a single line \( i \) as

\[
I_i(x_i, k) = \Pr(X_i > x_i + k) = 1 - F_i(x_i + k)
\] (4)

and

\[
D_i(x_i, k) = \int_{x_i+k}^{\infty} t - (x_i + k) \, dF_i(t).
\] (5)
In both of these equations $x_i$ is performing double duty: it is the mean of $X_i$ and in $x_i + k$ it determines where $F_i$ is evaluated. To emphasize this we could write

$$I_i(x_i, k) = 1 - F_i(x_i + k; x_i).$$

Finally, let $X = X_1 + \cdots + X_n$ be the total losses with distribution function $F$. Define insolvency and deficit functions for the whole company as

$$I(x_1, \ldots, x_n, k) = \Pr(\sum X_i > \sum x_i + k) = 1 - F(x_1 + \cdots + x_n + k)$$

(7)

and

$$D(x_1, \ldots, x_n, k) = \int \cdots \int_{\sum t_i > \sum x_i + k} t_1 + \cdots + t_n - (x_1 + \cdots + x_n + k) \, dF(t_1, \ldots, t_n).$$

(8)

The following definition is key:

**Definition 1** A family of random variables $X(x)$ with $E(X(x)) \propto x$ is called **homogeneous** if there exists a single random variable $U$ so that $X(x)/x$ has the same distribution as $U$ for all $x$.

Homogeneity is Myers and Read’s only distributional assumption, and it means that losses come from a representative insurer. The requirement that $U$ is independent of $x$ is important—after all, any random variable can be written as $X = E(X)(X/E(X))!$ An exponential variable $X$ with mean $x$ is a homogeneous family, since $X = xU$ where $U$ has an exponential distribution with mean $1$. However, a normal variable with mean $x$ and standard deviation $1$ is not homogeneous.
In order to compute expressions like $\partial I/\partial x$ we need to know how the family $X(x)$ changes shape with changes in $x$. We need to work with $X(x + \epsilon)$ as well as $X(x)$ because

$$
\frac{\partial I}{\partial x} = -\frac{d}{dx} F(x + k; x) \\
= -\lim_{\epsilon \to 0} \frac{F(x + k + \epsilon; x) - F(x + k; x)}{\epsilon} \\
- \lim_{\epsilon \to 0} \frac{F(x + k; x + \epsilon) - F(x + k; x)}{\epsilon}.
$$

The partial derivative has a static part, where the mean of the underlying variable does not change, and a dynamic part, where the point of evaluation is fixed but the mean changes. This shows computing partial derivatives such as $\partial I/\partial x$ is inextricably linked to families of random variables.

With this notation we can now state our main result.

**Proposition 1** The following are equivalent.

1. For each $i = 1, \ldots, n$, $X_i(x_i)$ is a homogeneous family of random variables.

2. For each $i = 1, \ldots, n$

$$
x_i \frac{\partial I_i}{\partial x_i} + k \frac{\partial I_i}{\partial k} = 0. \quad (9)
$$

3. For each $i = 1, \ldots, n$

$$
x_i \frac{\partial D_i}{\partial x_i} + k \frac{\partial D_i}{\partial k} = D. \quad (10)
$$

4. We have equality

$$
x_1 \frac{\partial I}{\partial x_1} + \cdots + x_n \frac{\partial I}{\partial x_n} + k \frac{\partial I}{\partial k} = 0. \quad (11)
$$
5. We have equality

$$x_1 \frac{\partial D}{\partial x_1} + \cdots + x_n \frac{\partial D}{\partial x_n} + k \frac{\partial D}{\partial k} = D. \quad (12)$$

The proposition says that each of the five statements holds if and only if all the other four hold. Put another way, if one of the five fails to hold then the other four will also fail. This means that we can construct simple one-line examples and can use items 2 and 3 generalize to the multi-line case. This simplifies the mathematics of the examples.

**Proof** We shall prove (4) implies (2) implies (1) implies (4), and then (5) implies (3) implies (1) implies (5), which is enough to show all the statements are equivalent.

(4) implies (2): Set $x_j = 0$ for $j \neq i$ in Equation (11) to get Equation (9). This can also be seen geometrically using Lemma 1 which says $I$ is constant along lines through the origin. Therefore $I_i$, which is a restriction of $I$, is also constant along such lines.

(2) implies (1): Lemma 1 applied to $I_i$ shows there exists a function $\tilde{I}_i$ so that

$$I_i(x_i, k) = \tilde{I}_i(k/x_i).$$

Let $U_i = X_i/x_i$, then $Pr(U_i > u) = \tilde{I}_i(u - 1)$ is independent of $x_i$ as required.

(1) implies (4): Assumption (1) implies that $I$ is constant along lines through the origin, so the result follows from Lemma 1.

(5) implies (3): Set $x_j = 0$ for $j \neq i$ in Equation (12) to get Equation (10).
(3) implies (1): Let $U_i = X_i/x_i$. We have to show $\Pr(U_i > u)$ is independent of $x_i$. Let $x^+ = \max(x, 0)$. Then, notice that

$$
\frac{\partial D}{\partial k} = \frac{\partial}{\partial k} E[(\sum x_i U_i - (\sum x_i + k))^+] \quad (13)
$$

$$
= E[\frac{\partial}{\partial k} (\sum x_i U_i - (\sum x_i + k))^+] \quad (14)
$$

$$
= E[-1_{\{\sum x_i U_i > \sum x_i + k}\}] \quad (15)
$$

$$
= -\Pr(\sum x_i U_i > \sum x_i + k) \quad (16)
$$

is minus the probability of default. Next, use Lemma 2 to define $\tilde{D}_i$ so that $D_i(x_i, k) = x_i \tilde{D}_i(k/x_i)$. Therefore

$$
\frac{\partial D_i}{\partial k} = \tilde{D}_i'(k/x_i)
$$

and so

$$
\Pr(U_i > u) = -\tilde{D}_i'(u - 1)
$$

is independent of $x_i$ as required.

(1) implies (5): Assumption (1) shows we can write $D$ as

$$
D(x_1, \ldots, x_n, k) = k \tilde{D}(x_1/k, \ldots, x_n/k)
$$

so the result follows from Lemma 2. □

The results in Proposition 1 are clearly similar to Myers and Read’s results but they are not exactly the same. We shall now explain how to explicitly derive their result and prove some other similar results. For simplicity we shall assume $n = 2$ and work with just $x_1$ and $x_2$ in the rest of the paper.
Myers and Read’s “adds-up” result (their Equation A1-3) involves computing the marginal increase in surplus required to hold the default value constant, given a marginal increase in a particular line. We have been taking a slightly different approach: if we hold the surplus and default value constant, what decrease is needed in line 2 to offset an increase in line 1? However, it is easy to reconcile the two approaches. To do this, let $\kappa_1$ and $\kappa_2$ be the marginal surplus requirements for each line. Note that $\kappa_1$ and $\kappa_2$ are ratios whereas $k$ is a dollar amount. Myers and Read then use a capital amount $k = \kappa_1 x + \kappa_2 x_2$ and define the default value $D_M$ (to distinguish from our $D$) as
\[
D_M(x_1, x_2) := D(x_1, x_2, \kappa_1 x_1 + \kappa_2 x_2).
\] (17)

Myers and Read use the following notation in their Appendix 1. They write $\tilde{L}_a = L_a \tilde{R}_a$, where $L_a$ corresponds to our $x_1$, $\tilde{R}_a$ to $U_1$ and $\tilde{L}_a$ to $X_1$. Thus $\tilde{L}_a = L_a \tilde{R}_a$ translates into our $X_1 = x_1 U_1$, i.e. the homogeneity assumption. The value $L_a$ is the expected value of $\tilde{L}_a$ at time 0. We are ignoring the time value of money here by assuming an interest rate of zero. Myers and Read also work with a fixed interest rate and then integrate over all possible rates—an extra level of sophistication that need not concern us.

We can now prove their result.

**Corollary 1** *(Myers and Read)* Assume losses $X_i$ form a homogeneous family for each $i$. Then default values “add-up” in that
\[
x_1 \frac{\partial D_M}{\partial x_1} + x_2 \frac{\partial D_M}{\partial x_2} = D_M.
\] (18)
Proof  Computing using the chain-rule and then applying Proposition 1 item 5 in Equation (19) gives:

\[
x_1 \frac{\partial D_M}{\partial x_1} + x_2 \frac{\partial D_M}{\partial x_2} = x_1 \left( \frac{\partial D}{\partial x_1} + \kappa_1 \frac{\partial D}{\partial \kappa} \right) + x_2 \left( \frac{\partial D}{\partial x_2} + \kappa_2 \frac{\partial D}{\partial \kappa} \right) \\
= x_1 \frac{\partial D}{\partial x_1} + x_2 \frac{\partial D}{\partial x_2} + \left( \kappa_1 x_1 + \kappa_2 x_2 \right) \frac{\partial D}{\partial \kappa} \\
= D(x_1, x_2, \kappa_1 x + \kappa_2 x) \\
= D_M(x_1, x_2)
\]

as required. □

Simple Proof  Here is the simple, self-contained proof we promised in the introduction. Dividing through by \(x_1\) in the definition of \(D\), Equation (8), it is clear that \(D_M(x_1, x_2) = x_1 \tilde{D}_M(x_2/x_1)\) for some function \(\tilde{D}_M\). Thus

\[
x_1 \frac{\partial D_M}{\partial x_1} + x_1 \frac{\partial D_M}{\partial x_1} = x_1 \left( \tilde{D}_M - \frac{x_2}{x_1} \frac{\partial D_M}{\partial x_1} \right) + x_2 \frac{\partial D_M}{\partial x_2} \\
= D_M
\]

which completes the proof. □

We now prove two more Myers and Read-like results which follow easily from Proposition 1. Using the implicit function theorem, Burkill and Burkill (1980), there is a function \(K(x_1, x_2)\) so that \(I(x_1, x_2, K(x_1, x_2)) = c\) is a constant.

Corollary 2  Assume losses \(X_i\) form a homogeneous family for each \(i\). Then surplus values defined by constant probability of default “add-up” in that

\[
x_1 \frac{\partial K}{\partial x_1} + x_2 \frac{\partial K}{\partial x_2} = K.
\]

(19)
Proof Proposition 1 implies
\[ x_1 \frac{\partial I}{\partial x_1} + x_2 \frac{\partial I}{\partial x_2} + k \frac{\partial I}{\partial k} = 0. \tag{20} \]
By the implicit function theorem
\[ \frac{\partial K}{\partial x_1} = -\frac{\partial I}{\partial x_1} / \frac{\partial I}{\partial k} \tag{21} \]
and similarly for \( x_2 \). Rearranging Equation (20) and substituting Equation (21) gives
\[ x_1 \frac{\partial K}{\partial x_1} + x_2 \frac{\partial K}{\partial x_2} = K, \tag{22} \]
so surplus values “add-up” just as Myers and Read’s default values add-up. □

Next, use the implicit function theorem to define a function \( L(x_1, x_2) \) so that \( D(x_1, x_2, L(x_1, x_2)) = c \).

Corollary 3 Assume losses \( X_i \) form a homogeneous family for each \( i \). Then surplus values defined by constant expected policy holder deficit satisfy
\[ x_1 \frac{\partial L}{\partial x_1} + x_2 \frac{\partial L}{\partial x_2} = L + T \tag{23} \]
where \( T = TVaR(x_1 + x_2 + L(x_1 + x_2)) \) is the tail-value at risk beyond \( x_1 + x_2 + L(x_1 + x_2) \).

Proof Using the implicit function theorem again, and dividing Proposition 1 item 5 by \(-\partial D/\partial k\), we get
\[ x_1 \frac{\partial L}{\partial x_1} + x_2 \frac{\partial L}{\partial x_2} = L - D / \frac{\partial D}{\partial k}. \tag{24} \]
Thus, by Equation (16)
\[ x_1 \frac{\partial L}{\partial x_1} + x_2 \frac{\partial L}{\partial x_2} = L + T \]
where \( T \) is the tail-value at risk. □
4 Examples

By Proposition 1, we can give one-dimensional examples and know they will extend to the multivariate situation as expected. We make use of this simplification in several of the examples below.

4.1 Examples of Homogeneity

Homogeneous families can be made from a wide variety of continuous distributions. For example, varying the scale parameter $\theta$ and holding all other parameters constant for any of the distributions listed in Appendix A of Klugman, Panjer and Willmot (1998) which have a scale parameter $\theta$, will produce a homogeneous family. This includes suitable parameterizations of the transformed beta, Burr, generalized Pareto, Pareto, transformed gamma, gamma, Weibull, exponential, and inverse Gaussian. By Proposition 1, sums of selected from such families will also be homogeneous. Also, trivially, if $X$ is any distribution with mean 1 then $xX$ is a homogeneous family as $x$ varies.

For example if $X$ has an exponential distribution with mean $x$, so $\Pr(X > t) = \exp(-t/x)$, then $X = xU$ where $U$ has an exponential distribution with mean 1. This follows since

$$\Pr(X > t) = \exp(-t/x) = \Pr(U > t/x).$$

Here

$$I(x, k) = \Pr(X > x + k) = \exp(-k/x)/e$$

which clearly satisfies item 2 of Proposition 1.
4.2 Simple Example where Homogeneity Fails

It is easy to construct examples where the homogeneity assumption fails. All members of a homogeneous family have the same coefficient of variation, therefore a family with a non-constant coefficient of variation will not be homogeneous.

For example, let $X$ be normally distributed with mean $x$ and constant standard deviation 1. Then $X$ is not homogeneous. By definition $I(x, k) = 1 - \Phi(k)$ so

$$x \frac{\partial I}{\partial x} + k \frac{\partial I}{\partial k} = -k \phi(k) \neq 0,$$

where $\Phi$ and $\phi$ are the distribution and density for the standard normal.

If the reader is skeptical about using only one variable, he or she will find it easy to construct multivariate distribution examples using normal variables. For example, consider what Corollary 2 says when $X_1$ is distributed $N(x_1, 1)$ and $X_2$ is distributed $N(x_2, 1)$. $X_1 + X_2$ is distributed $N(x_1 + x_2, \sqrt{2})$, so

$I(x_1, x_2, k) = 1 - \Phi(k/\sqrt{2})$. \hspace{1cm} (25)$

Thus $\partial K/\partial x_i = (\partial I/\partial x_i)/(\partial I/\partial k) = 0$ for $i = 1, 2$. Corollary 2 then reads $K = 0$, which is absurd! This shows the importance of the homogeneity assumption for the results derived from Proposition 1, including Myers and Read’s allocation formula. This example can also be generalized to the case where $X_1$ and $X_2$ are correlated.
4.3 Homogeneity Fails with Constant Coefficient of Variation

It is less simple, but still possible, to construct examples where the coefficient of variation is a constant function of the mean, but which nevertheless fail to satisfy the homogeneity assumption.

For example let $X(x)$ be distributed as a gamma random variable with parameters $\alpha = 4x^2$, $\theta = 1/2$ shifted by $x(1 - 2x)$. Here we are using the Klugman, Panjer, Willmot parameterization so $f(t; \alpha, \theta) = (t/\theta)^{\alpha-1} e^{-t/\theta} / \Gamma(\alpha)$. It is easy to check $X(x)$ has mean $x$, constant coefficient of variation 1 and skewness $1/x$, since the skewness of a gamma $\alpha, \theta$ is $2/\sqrt{\alpha}$. $I$ is given by the incomplete gamma function, $I(x, k) = \Gamma(4x^2, 4x^2 + 2k)$, which does not satisfy the assumptions of Lemma 1, so $X(x)$ is not homogeneous. The reason is clear: the family $X(x)$ changes shape with $x$ and so cannot be homogeneous.

Taking this a step further, it is possible to construct a family all of whose higher cumulants (coefficient of variation, skewness, kurtosis, etc.) are independent of the mean, just as they would be for a homogeneous family, but which nevertheless fails to be homogeneous. To do this, let $U$ be a lognormal random variable with $\ln(U)$ distributed as a standard normal. Let $V$ be a random variable density function $f_V(x) = f_U(x)(1 + \sin(2\pi \log(x)))$, where $f_U$ is the density of $U$. Then $U$ and $V$ have the same moments—see Feller (1971), Chapter VII.3. This type of trick is possible because the moments of a lognormal grow too quickly to ensure it is determined by its moments—see also Billingsley (1986) Section 30. Let $X(x)$ be a mixture of $xU$ and $xV$ with weights $p(x) = x/(x + 1)$ and $1 - p(x)$. Then

$$I(x, k) := p(x)Pr(U > 1 + k/x) + (1 - p(x))Pr(V > 1 + k/x)$$
is not a function of $k/x$ so the result follows from Lemma 1 and Proposition 1. Alternatively, writing $I_U(x, k) = \Pr(xU > x + k)$ and similarly for $V$ one can compute directly

$$x \frac{\partial I}{\partial x} + k \frac{\partial I}{\partial k} = xp'(x)(I_U(x, k) - I_V(x, k)) \neq 0$$

since $xU$ and $xV$ are homogeneous, $xp'(x) > 0$ by construction, and $I_U - I_V \neq 0$. Thus $X(x)$ is not a homogeneous family.

### 4.4 Aggregate Distributions are Not Homogeneous

Example 4.1 shows a large number of continuous variables satisfy the homogeneity assumption. For our purposes, however, there is a very important class which does not: aggregate loss distributions.

Let $A = X_1 + \cdots + X_N$ where the $X_i$ are independent, identically distributed severities and $N$ is a frequency distribution with mean $n$. Increasing expected losses in this model involves increasing $n$. Suppose $N$ has contagion $c$, so, as suggested by Heckman and Meyers (1983), $\Var(N) = n(1 + cn)$. Then

$$\text{CV}(A)^2 = \frac{\text{CV}(X)^2}{n} + \frac{1}{n} + c$$

is clearly not independent of $n$. Thus $A$ does not satisfy the homogeneity assumption. Just as for Example 4.3, the aggregate loss distribution changes shape as $n$ increases. This is illustrated in the figure below, which shows six aggregate loss distributions with the same severity distribution but different claim counts, indicated by “CC=20” for $n = 20$, and so forth. The individual densities have
been scaled so that if the family were homogeneous then all the densities would be identical and only one line would appear in the plot.

If aggregate distributions can be approximated by various of the parametric distributions of Example 4.1, and if those distributions are homogeneous, does the result of this Example really matter? The answer is emphatically “yes”. This example shows that in the real world, where insurers grow by adding discrete insureds, the “adds-up” results do not hold. The way the aggregate distribution changes shape forces parameters other than the scale parameter to change as the mean increases, and thus homogeneity is lost.

4.5 Compound Poisson Distributions are not Homogeneous

This example proves that various aggregate distributions can never be homogeneous families.
**Proposition 2** Let $A$ be a compound Poisson aggregate distribution

$$A = X_1 + \cdots + X_N$$  \hspace{1cm} (26)

where $N$ has a Poisson distribution with mean $n$ and the $X_i$ are independent and identically distributed. Then $A(n)$ is not a homogeneous family.

**Proof** The moment generating function of $N$ is $M_N(t) = \exp(n(e^t - 1))$. The moment generating function of $A$ is therefore $M_A(t) = \exp(n(M_X(t) - 1))$ where $M_X$ is the moment generating function for severity $X$. If $A$ is homogeneous with $A$ distributed as $nU$ for some fixed $U$, then $M_A(t) = M_U(nt)$. Thus

$$n(M_X(t) - 1) = \log(M_U(nt)).$$

Differentiating with respect to $n$ shows

$$(M_X(t) - 1) = tM'_U(nt)/M_U(nt).$$

Therefore $M'_U(t)/M_U(t)$ must be a constant, since the left hand side is independent of $n$. Hence $M_U(t) = \exp(ct)$ for a constant $c$, and so $U = c$ is a degenerate distribution. But this is impossible unless $N$ is constant or $X_i \equiv 0$. □

**Corollary 4** An aggregate distribution with frequency component $N$ which is a mixture of Poisson distributions cannot be a homogeneous family.

**Proof** Condition on the mixing parameter and apply Proposition 2. □

For example, the Corollary applies to negative binomial and Poisson-inverse Gaussian frequency distributions.
4.6 Optimization

An insurance company should substitute line 1 for line 2 if the increase in profits from writing more of line 1 is greater than the loss of profits from writing less of line 2, holding the probability of default constant. This type of optimization, achieved using Lagrangian multipliers, has already been introduced to actuaries by Meyers (1991) who uses a standard deviation constraint in place of an insolvency or policy holder deficit constraint. Converting to a probability of default constraint will lead naturally to mathematical expressions similar to those in this note, regardless of the applicability of the “adds-up” argument.

We can also consider optimization over both volume by line of business and the amount of capital held by the insurance company. This is an interesting generalization because it will make predictions about optimal leverage ratios and industry concentration, and because it highlights the importance of the changing shape of aggregate loss distributions for changing expected losses. I will return to this question in a subsequent paper.

The optimization approach does not solve the surplus allocation problem, which must be done in order to allocate the tax-on-surplus burden to each line of business.

5 Conclusions

In this paper we have explained the importance of the homogeneity assumption in the derivation of Myers and Read’s “adds-up” result. Proposition 1 shows the assumption is necessary as well as sufficient. We have used Proposition 1 to prove
two other results in a similar vein, including one involving tail value at risk. Importantly, for practical applications, we have shown that most common families of aggregate distributions will never satisfy the homogeneity assumption. Therefore, in a real-world situation, where insurers grow by adding individual risks from discrete insureds, the “adds-up” result will not hold.

References


