

RISK-SHARING RULES AND THEIR PROPERTIES, WITH APPLICATIONS TO PEER-TO-PEER INSURANCE

Michel Denuit, Jan Dhaene, Christian Y. Robert

REPRINT | 2022 / 26

ISBA

Voie du Roman Pays 20 - L1.04.01

B-1348 Louvain-la-Neuve

Email : lidam-library@uclouvain.be

<https://uclouvain.be/en/research-institutes/lidam/isba/publication.html>

RISK-SHARING RULES AND THEIR PROPERTIES, WITH APPLICATIONS TO PEER-TO-PEER INSURANCE

MICHEL DENUIT

Institute of Statistics, Biostatistics and Actuarial Science - ISBA
Louvain Institute of Data Analysis and Modeling - LIDAM
UCLouvain
Louvain-la-Neuve, Belgium
`michel.denuit@uclouvain.be`

JAN DHAENE

Actuarial Research Group, AFI
Faculty of Business and Economics
KU Leuven
B-3000 Leuven, Belgium
`jan.dhaene@econ.kuleuven.ac.be`

CHRISTIAN Y. ROBERT

Laboratory in Finance and Insurance - LFA
CREST - Center for Research in Economics and Statistics
ENSAE
Paris, France
`chrobert@ensae.fr`

November 23, 2021

Abstract

This paper offers a systematic treatment of risk-sharing rules for insurance losses, based on a list of relevant properties. A number of candidate risk-sharing rules are considered, including the conditional mean risk-sharing rule proposed in Denuit and Dhaene (2012) and the newly introduced quantile risk-sharing rule. Their compliance with the proposed properties is established. Then, methods for building new risk-sharing rules are discussed. The results derived in this paper are shown to be helpful in the development of peer-to-peer insurance (or crowdsurance), as well as to manage contingent risk funds where a given budget is distributed among claimants.

Keywords: pooling, peer-to-peer (P2P) insurance, crowdsurance, conditional mean risk-sharing rule, quantile risk-sharing rule, comonotonicity.

1 Introduction and motivation

In a risk-sharing pool, each participant is compensated from the pool for his or her individual losses. In return, he or she pays an ex-post contribution to the pool, which is determined so that the sum of all the individual contributions matches the aggregate loss of the pool. The simplest case arises when the pool is homogeneous (i.e. the individual losses are identically distributed) and comprises exchangeable losses. In this case, a natural risk-sharing rule consists of every participant contributing ex-post an equal part of the aggregate loss and the latter is thus distributed uniformly over all pool members. We refer the reader to Albrecht and Huggenberger (2017) for a thorough investigation of the homogeneous case.

The problem to find an appropriate and simple risk-sharing rule in the heterogeneous case appears to be considerably more complex. For insurance purposes, some degree of standardization is needed so that risk sharing cannot integrate all aspects of individual preferences (e.g. individual utility functions) but only general behavioral traits, such as risk aversion. In this setting, Denuit and Dhaene (2012) introduced and investigated the conditional mean risk-sharing rule, where each participant contributes the conditional expectation of the loss brought to the pool, given the aggregate loss covered by the pool. The properties of this risk-sharing rule have been further explored by Denuit (2019, 2020) and Denuit and Robert (2020, 2021a-h).

Recently, risk sharing has been re-visited in the context of peer-to-peer (P2P) insurance or crowdsurance. P2P insurance refers to risk sharing networks where a group of individuals pool their resources together to insure against a given peril. P2P insurance systems so revive the ancestral compensation mechanism consisting in using the contributions of the many to balance the misfortunes of the few. See, e.g., Abdikerimova and Feng (2021) and the references therein. Such risk-sharing mechanisms are also found in mutual insurance arrangements or partnerships among lawyers, farmers, or physicians for instance, who form risk pools to protect themselves against professional risks. Natural catastrophes and major industrial risks (e.g., induced by nuclear plants) are also typically covered by funds or pools where risk sharing operates. There is thus a clear need for a better understanding of risk-sharing rules to support the development of these emerging markets or strengthen the resilience against major risks.

Inspired by the literature devoted to premium calculation principles and risk measures, we propose a list of desirable properties for risk-sharing rules and we analyze the compliance of the conditional mean risk-sharing rule and the newly introduced quantile risk-sharing rule with this list. We also explain how to generate new risk-sharing rules by combining or adapting existing ones in various ways. This also allows us to bridge seemingly unrelated risk-sharing rules.

Notice that other authors have proposed relevant properties for risk sharing. For instance, Hieber and Lucas (2020) imposed self-sufficiency, positivity and fairness for the distribution of mortality credits in their modern life-care tontines. In economics, Bourles et al. (2021) studied the implications of altruistic transfers in risk sharing. As far as we are aware, most properties proposed in the present paper have not yet been formalized in the literature devoted to risk sharing and open the door to a more systematic treatment of risk-sharing rules for insurance losses. We do not address the related problem of capital allocation which requires the specification of risk measures for every participant. Considering personal

insurance lines, it seems indeed difficult that participants elicit risk measures governing their individual choices. We refer the reader e.g. to Filipovic and Svindland (2008) for a nice exposition and the connection between optimal capital and risk allocations. Let us also mention the contribution by Embrechts et al. (2018) who characterize (Pareto-)optimal risk-sharing rules, where the (Pareto-)optimality is expressed in terms of a sum of quantile-based risk measures applied to the individual losses in the pool. The approach in the present paper is different as we investigate properties that risk-sharing rules may or may not obey, and we determine the properties of some existing as well as newly introduced risk-sharing rules. Several papers have also been devoted to cost sharing, adopting a game theoretic perspective. See e.g. Chen et al. (2017) for an application of this approach to risk sharing. These authors proposed two properties for an allocation rule: stability and monotonicity employing concepts of core and population monotonicity from cooperative game theory. Stability requires that no participant would face lower risk if he or she were alone rather than participating in the pool. Monotonicity requires that a new entry will not lead to higher risks allocated to existing participants. These concepts are very appealing but they appear to be difficult to transpose in the setting of this paper because they also require introducing risk measures. We come back to this issue in the concluding section.

Under pure P2P insurance, participants' contributions are theoretically unlimited. To avoid counterparty risk and to be able to deal with larger sums insured, Denuit (2020) replaced unlimited ex-post contributions with a deposit paid ex ante combined with an ex-post bonus mechanism restoring fairness, with the guarantee that the final amount due never exceeds this down payment. Part of the deposit feeds a common fund, while the remaining part is paid to a partnering insurance or reinsurance company. If the common fund is insufficient to pay for the claims then the (re-)insurance carrier pays the excess. Conversely, if the pool has few claims then the surplus is given back to the participants or to a cause the pool members care about. Denuit (2020) designed this scheme under the conditional mean risk-sharing rule and we extend it here to any rule satisfying some desirable properties among those proposed in this paper.

The remainder of the text is organized as follows. Section 2 precisely defines risk sharing and risk-sharing rules. Some simple examples are given which are further used to illustrate the properties listed in Section 3. Section 4 is devoted to the conditional mean risk-sharing rule. After having recalled its definition, we study its compliance with the properties proposed in Section 3. Section 5 introduces the new quantile risk-sharing rule, where participants all contribute the quantile at the same probability level of their individual losses. The properties of this new risk-sharing rule are thoroughly investigated. Section 6 proposes different modifications to the conditional mean risk-sharing rule, resulting from a distribution change agreed by participants before risk sharing operates. This allows us to relate several existing risk-sharing rules, which offers a better understanding of their respective properties. In Section 7, we study the business model underlying the majority of P2P insurance schemes which essentially reduce to a shared, or pooled deductible where the lower layer is covered by the participants whereas the upper layer is transferred to an insurer. Section 8 generates new risk-sharing rules from existing ones, by convex combination, network structure, collectivization of the pool or restriction of the risk sharing to claimant participants. The latter approach applies to contingent risk funds where individuals contribute ex ante a fixed amount that is distributed ex post among those participants having experienced a pre-defined event.

The final Section 9 discusses the results in connection to commercial insurance and emerging P2P insurance. The proofs of the main results are gathered in the appendix.

2 Risk sharing and risk-sharing rules

Consider n individuals, numbered $i = 1, 2, \dots, n$. Each of them is exposed to some peril causing a random non-negative monetary loss at the end of a given observation period, taken to be the time interval $(0, 1)$. Let us denote the loss of person i by $X_i \geq 0$. Unless stated otherwise, we assume that the random variables X_i have finite means. These losses are defined on a common probability space $(\Omega, \mathcal{F}, \mathbb{P})$. We assume that this space is rich enough to contain all the random variables mentioned throughout the text. A n -dimensional random vector of losses $\mathbf{X}_n = (X_1, X_2, \dots, X_n)$ will be called a pool (of losses). The joint (cumulative) distribution function of the pool $\mathbf{X}_n$ is denoted by $F_{\mathbf{X}_n}$, the marginal distribution functions of the individual losses being denoted by $F_1, F_2, \dots, F_n$, respectively. The total loss faced by the n participants in the pool $\mathbf{X}_n$ is denoted by $S_n = \sum_{i=1}^n X_i$. Throughout the paper, all equalities and inequalities between random variables are assumed to hold almost surely. Similarly, (in-)equalities between random vectors are meant to hold componentwise and almost surely. The latter are not to be confused with stochastic inequalities (corresponding to convex order in this paper).

Without any insurance or risk-sharing agreement, any individual bears his or her own loss, which means that individual i suffers the loss x_i , where x_i stands for the realization of X_i , which will be observed at time 1. Throughout this paper, we make the notational convention that a random variable is denoted by an upper-case letter (e.g. X_i), while its realization (observed at time 1) is generally denoted by the corresponding lower-case letter (e.g. x_i). A random vector is denoted by a bold upper-case letter with subscript indicating its dimension (e.g. $\mathbf{X}_n$), while its realization (known at time 1) is denoted by the corresponding bold lower-case small letter (e.g. $\mathbf{x}_n$).

Let us now assume that instead of each individual bearing his or her own risk, the participants in the pool $\mathbf{X}_n$ decide to share their risks. Following von Bieberstein et al. (2019), we focus in this paper on formal risk pools where losses are observable and risk sharing among members can be specified in an explicit and perfectly enforceable contract, in the sense of the following definitions.

Definition 2.1 (risk sharing). *Risk sharing in a pool $\mathbf{X}_n = (X_1, X_2, \dots, X_n)$ is a two-stage process. In the ex-ante step at time 0, the random losses comprised in the pool $\mathbf{X}_n$ are re-allocated by transforming $\mathbf{X}_n$ into another random vector $\mathbf{H}(\mathbf{X}_n)$ of the same dimension:*

$$\mathbf{H}(\mathbf{X}_n) = (H_1(\mathbf{X}_n), H_2(\mathbf{X}_n), \dots, H_n(\mathbf{X}_n)), \quad (2.1)$$

where all $H_i(\mathbf{X}_n) \geq 0$, and such that the full allocation property

$$\sum_{i=1}^n H_i(\mathbf{X}_n) = \sum_{i=1}^n X_i \quad (2.2)$$

is satisfied.

The ex-post step takes place at time 1, at the moment that the realization $\mathbf{x}_n = (x_1, x_2, \dots, x_n)$ of the pool $\mathbf{X}_n$ is observed. At that time, each participant i to the pool $\mathbf{X}_n$ receives the realization x_i of his or her loss X_i from the pool. In return, each participant i contributes to the pool the realization $H_i(\mathbf{x}_n)$ of his or her re-allocated loss $H_i(\mathbf{X}_n)$.

We are now ready to provide a formal definition of risk-sharing rules.

Definition 2.2 (risk-sharing rule). *A risk-sharing rule $\mathbf{H}$ is a mapping which transforms any pool $\mathbf{X}_n$ into another random vector $\mathbf{H}(\mathbf{X}_n)$ of the same dimension, see (2.1), where all $H_i(\mathbf{X}_n) \geq 0$, and such that the full allocation condition (2.2) is satisfied.*

Some risk-sharing rules $\mathbf{H}$ depend on individual losses X_i only through the aggregate loss S_n . They are said to be aggregate risk-sharing rules. We refer the reader to Feng et al. (2020) for a discussion of this kind of rule, in comparison with general ones. For an aggregate risk-sharing rule $\mathbf{H}$, we will often use the simpler notation $\mathbf{H}(S_n)$ for $\mathbf{H}(\mathbf{X}_n)$.

Depending on the risk-sharing rule under consideration, $\mathbf{H}$ may require the knowledge of the joint distribution function $F_{\mathbf{X}_n}$ of $\mathbf{X}_n$ or just of a set of parameters (such as the mean values, for instance). By a slight abuse of notation, we keep the simple notation $H_i(\mathbf{X}_n)$ for the amount allocated to participant i , without referring explicitly to the underlying joint distribution function or parameter values.

Let us now have a look at some simple examples of risk-sharing rules that will be used to illustrate the properties listed in the next section. The first one corresponds to the case where individuals do not pool their risks.

Example 2.3 (stand-alone risk-sharing rule). *The case where each participant in the pool bears his or her own risk can be described by the straightforward risk-sharing rule*

$$\mathbf{H}(\mathbf{X}_n) = \mathbf{X}_n. \quad (2.3)$$

This is just the stand-alone situation where each agent keeps his or her own initial loss. The pool just acts as a register to collect data about individual losses, without re-allocating them among participants.

The most simple and well-known risk-sharing rule consists of equally sharing the aggregate loss S_n . In this case, S_n is uniformly distributed over all participants, leading to the following risk-sharing rule.

Example 2.4 (uniform risk-sharing rule). *The uniform risk-sharing rule $\mathbf{H}^{\text{uni}}$ is an aggregate risk-sharing rule defined as*

$$H_i^{\text{uni}}(\mathbf{X}_n) = H_i^{\text{uni}}(S_n) = \frac{S_n}{n}, \quad i = 1, 2, \dots, n. \quad (2.4)$$

Individual contributions are thus equal for all participants.

Linear schemes have been widely used in a risk-sharing context in practice. In this case, participants agree to pay the pure premium $E[X_i]$ and to divide deviations of S_n from the total pure premium $E[S_n]$ (positive or negative) in proportion to some positive coefficients $a_{i,n}$ summing to 1. Precisely, participant i contributes $E[X_i] + a_{i,n}(S_n - E[S_n])$. The numbers

$a_{i,n}$ are called participation coefficients by Schumacher (2018). The design of the allocation scheme then amounts to select an appropriate set of participation coefficients $a_{i,n}$. Clearly, such linear schemes allocate the full risk S_n but can also generate negative values, which contradicts our Definition 2.1. If there is no loss at all, i.e. if $S_n = 0$, then the linear regression rule would still force all participants to exchange cash which is not reasonable since there is no loss to compensate for. For these reasons, we restrict our analysis of linear schemes to proportional rules as the following one.

Example 2.5 (mean proportional risk-sharing rule). *The mean proportional risk-sharing rule $\mathbf{H}^{\text{prop}}$ is an aggregate risk-sharing rule defined as*

$$H_i^{\text{prop}}(\mathbf{X}_n) = H_i^{\text{prop}}(S_n) = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n]} S_n, \quad i = 1, 2, \dots, n.$$

Participants adopting $\mathbf{H}^{\text{prop}}$ thus agree to take a fixed percentage of the total loss S_n , in accordance with the expected values of the risks they bring to the pool compared to the total expected loss. In particular, if all expected losses $\mathbb{E}[X_i]$ are equal then $H_i^{\text{prop}}(\mathbf{X}_n) = H_i^{\text{uni}}(\mathbf{X}_n)$.

The idea behind the following two risk-sharing rules is that participants can be ranked according to any relevant characteristic reflecting their risk-bearing capacity, and losses are allocated to them according to their magnitude.

Example 2.6 (order statistics risk-sharing rule). *Recall that order statistics, denoted as $X_{(i)}$, correspond to the components of $\mathbf{X}_n$ ranked in ascending order, that is, $X_{(1)} \leq X_{(2)} \leq \dots \leq X_{(n)}$. Under the order statistics risk-sharing rule for a pool $\mathbf{X}_n$, the re-allocated loss vector is defined by*

$$\mathbf{H}^{\text{ord}}(\mathbf{X}_n) = (X_{(1)}, X_{(2)}, \dots, X_{(n)}). \quad (2.5)$$

Considering for instance age as an indicator of financial strength, the largest loss $X_{(n)}$ could be allocated to the oldest participant, numbered n , the second-largest $X_{(n-1)}$ to the second-oldest numbered $n-1$, and so on. The risk-sharing rule $\mathbf{H}^{\text{ord}}$ is not an aggregate risk-sharing rule.

Example 2.7 (multiple layer risk-sharing rule). *Consider increasing limits $0 < d_1 < d_2 < \dots < d_{n-1}$ defining layers for the total loss S_n , irrespective of the distribution of $X_1, X_2, \dots, X_n$. Under the multiple layer risk-sharing rule, the re-allocated loss vector for any $\mathbf{X}_n$ is defined by*

$$\mathbf{H}^{\text{layer}}(\mathbf{X}_n) = \mathbf{H}^{\text{layer}}(S_n) = (\min\{S_n, d_1\}, (S_n - d_1)_+ - (S_n - d_2)_+, \dots, (S_n - d_{n-1})_+). \quad (2.6)$$

Participant i thus covers that part of the aggregate loss S_n in the layer (d_{i-1}, d_i) , setting $d_0 = 0$ and $d_n = \infty$.

Notice that another possibility would be to let the limits d_i depend on the (distribution of the) total losses comprised in the pool, for instance by taking for d_i the quantile at level i/n of S_n . In the definition of the multiple layer risk-sharing rule, the limits are defined without reference to the total losses and reflect participants risk-bearing capacities.

For applying the uniform, the order statistics or the multiple layer risk-sharing rules, we do not need to know anything about the joint distribution function $F_{\mathbf{X}_n}$ of $\mathbf{X}_n$. These rules are thus free of model risk but are not necessarily reasonable choices, depending on the circumstances. The mean proportional risk-sharing rule depends on the joint distribution function $F_{\mathbf{X}_n}$ of $\mathbf{X}_n$ through expected values, only.

3 Properties of risk-sharing rules

Goovaerts et al. (1984) pioneered the systematic study of the properties that any premium principle should/could possess. Afterwards, numerous authors suggested various requirements that any risk measure should/could satisfy. The interested reader is referred to Denuit et al. (2005) for a general account of the topic. We provide hereafter a list of reasonable (not necessarily independent) requirements that a risk-sharing rule should/could fulfill and discuss their interpretation. Some requirements are directly inspired from premium calculation principles or risk measures, whereas others are tailored to risk-sharing rules.

3.1 Reshuffling

Let π be a permutation of $\{1, \dots, n\}$. We say that the pool $\mathbf{X}_n$ is reshuffled into the pool $\mathbf{X}_n^\pi$ if both random vectors are composed of the same individual losses, but only their places are interchanged, that is, $\mathbf{X}_n^\pi = (X_{\pi(1)}, X_{\pi(2)}, \dots, X_{\pi(n)})$. The reshuffling property expresses the idea that the order in which the individual participants are considered does not change their contribution. This is precisely stated next.

Definition 3.1 (reshuffling property). *A risk-sharing rule $\mathbf{H}$ satisfies the reshuffling property if for any pool $\mathbf{X}_n$ and any of its reshuffled versions $\mathbf{X}_n^\pi$, one has that*

$$\pi(i) = j \Rightarrow H_i(\mathbf{X}_n) = H_j(\mathbf{X}_n^\pi) \text{ for any } i = 1, \dots, n. \quad (3.1)$$

Example 3.2. *The uniform risk-sharing rule satisfies the reshuffling property since individual contributions are equal for all participants.*

Example 3.3. *The mean proportional rule satisfies the reshuffling property since*

$$\pi(i) = j \Rightarrow H_i^{\text{prop}}(\mathbf{X}_n) = \frac{E[X_i]}{E[S_n]} S_n = H_j^{\text{prop}}(\mathbf{X}_n^\pi) \text{ for any } i = 1, \dots, n.$$

Example 3.4. *Neither the order statistics rule nor the multiple layer rule satisfy the reshuffling property since the numbering of participants reflects their risk-bearing capacity and the magnitude of losses or layer they assume.*

3.2 Normalization

For premium calculation principles, the normalization property means that a zero risk leads to a zero premium. From the full allocation condition (2.2) and the assumed non-negativity $H_i(\mathbf{X}_n) \geq 0$ for all i , we deduce that

$$X_i = 0 \text{ for all } i \Rightarrow H_i(\mathbf{X}_n) = 0 \text{ for all } i.$$

It seems reasonable to require that a participant bringing a zero loss should not contribute ex post to S_n . This is in essence the following property, which can be seen as an appropriate normalization property for risk-sharing rules.

Given a pool $\mathbf{X}_n = (X_1, X_2, \dots, X_n)$, the reduced pool without participant j will be henceforth denoted as

$$\mathbf{X}_{n-1}^{(\setminus j)} = (X_1, \dots, X_{j-1}, X_{j+1}, \dots, X_n), \quad j = 2, \dots, n-1, \quad (3.2)$$

with $\mathbf{X}_{n-1}^{(\setminus 1)} = (X_2, \dots, X_n)$ and $\mathbf{X}_{n-1}^{(\setminus n)} = (X_1, \dots, X_{n-1})$, by convention. We are now ready to state the following definition.

Definition 3.5 (normalization property). *A risk-sharing rule $\mathbf{H}$ satisfies the normalization property if for any pool $\mathbf{X}_n$ with $X_j = 0$ for some $j = 1, \dots, n$, one has that*

$$H_i(\mathbf{X}_n) = \begin{cases} H_i(\mathbf{X}_{n-1}^{(\setminus j)}) & \text{for } i = 1, \dots, j-1 \\ H_{i-1}(\mathbf{X}_{n-1}^{(\setminus j)}) & \text{for } i = j+1, \dots, n \end{cases} \quad (3.3)$$

where $\mathbf{X}_{n-1}^{(\setminus j)}$ is defined in (3.2), with the understanding that we only keep the second case in (3.3) when $j = 1$ and the first one when $j = n$.

Taking into account the full allocation condition (2.2), the normalization property (3.3) leads to

$$X_j = 0 \Rightarrow H_j(\mathbf{X}_n) = 0. \quad (3.4)$$

Considering (3.3)-(3.4), the normalization property means that individual contributions remain unchanged if a zero risk is added to the pool and that a zero risk has a zero contribution. This reasoning can be iterated so that we see that any subset of losses $X_j = 0$ can be excluded from the risk sharing when participants agree to use a risk-sharing rule satisfying the normalization property.

Remark 3.6. If the risk-sharing rule satisfies the reshuffling property then the normalization property can be defined by considering only a given participant, for instance the last one. Precisely, a risk-sharing rule $\mathbf{H}$ satisfying the reshuffling property also satisfies the normalization property if for any pool $\mathbf{X}_n = (X_1, X_2, \dots, X_{n-1}, 0)$, one has that

$$H_i(\mathbf{X}_n) = H_i(\mathbf{X}_{n-1}) \quad \text{for all } i \neq n, \quad (3.5)$$

where $\mathbf{X}_{n-1} = (X_1, X_2, \dots, X_{n-1})$.

Example 3.7. *The uniform risk-sharing rule does not satisfy the normalization property. Considering for instance $n = 3$, we see that*

$$H_1^{\text{uni}}((X_1, X_2, 0)) = \frac{X_1 + X_2}{3} \neq \frac{X_1 + X_2}{2} = H_1^{\text{uni}}((X_1, X_2)).$$

Participant 3 bringing a zero loss to the pool must also contribute to total losses under the uniform rule.

Example 3.8. *The mean proportional rule satisfies the normalization property, as shown next. Since it satisfies the reshuffling property, it is enough to consider the last participant and establish the validity of (3.5). Clearly, $S_n = S_{n-1}$ when $\mathbf{X}_n = (X_1, X_2, \dots, X_{n-1}, 0)$ and $\mathbf{X}_{n-1} = (X_1, X_2, \dots, X_{n-1})$ so that $H_i^{\text{prop}}(\mathbf{X}_n) = H_i^{\text{prop}}(\mathbf{X}_{n-1})$ for $i = 1, \dots, n-1$. Moreover, $H_n^{\text{prop}}(\mathbf{X}_n) = 0$ since $E[X_n] = 0$ when $X_n = 0$.*

Example 3.9. *Neither the order statistics rule nor the multiple layer rule satisfy the normalization property since they are both based on a specific ranking for participants to the pool who are attributed a given order statistic or layer, whatever the loss they bring to the pool.*

3.3 Translativity

The property of translativity is often imposed on premium calculation principles as well as on risk measures. It basically means that adding a constant to a given loss shifts the premium and capital in a similar way. Hereafter, we define an adapted version of translativity for risk sharing. Let us introduce the notation $\mathbf{1}_{i,n}$ to indicate the n -dimensional vector $(0, 0, \dots, 0, 1, 0, 0, \dots, 0)$, with all components equal to 0, except the i th component which equals 1.

Definition 3.10 (translativity property). *A risk-sharing rule $\mathbf{H}$ satisfies the translativity property if for any pool $\mathbf{X}_n$ and any participant $j = 1, \dots, n$, one has that*

$$H_i(\mathbf{X}_n + c \mathbf{1}_{j,n}) = H_i(\mathbf{X}_n) \text{ for all } i \neq j \text{ and any } c \geq 0. \quad (3.6)$$

Translativity of a risk-sharing rule means that in case a particular participant's loss is increased by a deterministic amount $c \geq 0$, the contributions of the other participants remain unchanged. Applying the full-allocation property (2.2) to $\mathbf{X}_n$ and to $\mathbf{X}_n + c \mathbf{1}_{j,n}$, respectively leads to

$$H_j(\mathbf{X}_n + c \mathbf{1}_{j,n}) = H_j(\mathbf{X}_n) + c, \quad (3.7)$$

which means that any increase of X_j by a deterministic amount $c \geq 0$ results in the same increase of the contribution for participant j .

Remark 3.11. If the risk-sharing rule satisfies the reshuffling property, it is enough to consider a given participant to define the translativity property, for instance the last one $j = n$.

Despite its reasonableness, it turns out that translativity is not fulfilled by the simple risk-sharing rules considered so far (except the trivial stand-alone one).

Example 3.12. *The uniform risk-sharing rule does not satisfy the translativity property. Considering for instance $n = 3$, we see that*

$$H_1^{\text{uni}}((X_1, X_2, X_3 + c)) = \frac{S_3 + c}{3} \neq \frac{S_3}{3} = H_1^{\text{uni}}((X_1, X_2, X_3)).$$

Participants 1-2 must thus also contribute to the deterministic increase in the loss brought to the pool by participant 3.

Example 3.13. *The mean proportional rule does not satisfy the translativity property since, for all $i \neq n$,*

$$H_i^{\text{prop}}(\mathbf{X}_n + c \mathbf{1}_{n,n}) = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n + c]} (S_n + c) \neq \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n]} S_n = H_i^{\text{prop}}(\mathbf{X}_n).$$

The constant addition c is thus also shared among all participants under the mean proportional rule whereas for a risk-sharing rule satisfying the translativity property, it should be assumed by participant n , only.

Example 3.14. *Neither the order statistics rule (since adding a constant c to X_j may modify order statistics) nor the multiple layer rule satisfy the translativity property.*

Some risk-sharing rules satisfying the translativity property will be discussed in the next sections.

3.4 Positive homogeneity

Positive homogeneity for premium calculation principles and risk measures means that multiplying the risk under consideration with a positive constant implies multiplying the initial premium or capital value with the same constant. This property is often associated to independence with respect to the monetary unit used for calculation (and not to the currency, as often wrongly stated). It appears to be reasonable for risk-sharing rules too, and is formally defined as follows.

Definition 3.15 (positive homogeneity property). *A risk-sharing rule $\mathbf{H}$ satisfies the positive homogeneity property if for any pool $\mathbf{X}_n$, one has that*

$$H_i(c\mathbf{X}_n) = cH_i(\mathbf{X}_n) \text{ for all } i \text{ and any } c \geq 0. \quad (3.8)$$

Example 3.16. *The uniform risk-sharing rule satisfies the positive homogeneity property since*

$$H_i^{\text{uni}}(c\mathbf{X}_n) = \frac{cS_n}{n} = cH_i^{\text{uni}}(\mathbf{X}_n) \text{ for } i = 1, \dots, n.$$

Example 3.17. *The mean proportional and the order statistics rules both satisfy the positive homogeneity property.*

Example 3.18. *The multiple layer rule does not satisfy the positive homogeneity property since the limits d_j remain unchanged.*

Notice that the multiple layer rule fails to fulfill the positive homogeneity property because the limits d_j do not depend on the distribution of the losses comprised into the pool. Letting these limits correspond to quantiles of S_n , the positive homogeneity property would be satisfied.

3.5 Constancy

Let us now consider the case where the risk brought by one participant to the pool is not random, but equal to some constant c with probability 1. The case $c = 0$ corresponds to normalization.

Definition 3.19 (constancy property). *A risk-sharing rule $\mathbf{H}$ satisfies the constancy property if for any pool $\mathbf{X}_n$ with $X_j = c$ for some constant $c \geq 0$ and $j = 1, \dots, n$, one has that (3.3) holds true.*

Taking into account the full-allocation property (2.2), applied to $\mathbf{X}_n$ and $\mathbf{X}_{n-1}^{(\vee j)}$, respectively, it follows from Definition 3.19 that

$$H_j(\mathbf{X}_n) = c. \quad (3.9)$$

The constancy property means that in case the risk brought by participant j to the pool is equal to some non-negative constant c , then this participant should only contribute that amount c to the pool, whereas the contributions of the other participants are not depending on whether the constant is added to the pool or not.

Remark 3.20. If the risk-sharing rule satisfies the reshuffling property then the constancy property can be defined by only considering a given participant j in the pool with a constant loss $c \geq 0$, for instance, the last one with $j = n$.

As it was the case for translitivity, it turns out that the elementary risk-sharing rules considered so far do not satisfy the constancy property (except the trivial stand-alone one).

Example 3.21. *The uniform risk-sharing rule does not satisfy the constancy property. Considering for instance $n = 3$, we see that*

$$H_1^{\text{uni}}((X_1, X_2, c)) = \frac{X_1 + X_2 + c}{3} \neq \frac{X_1 + X_2}{2} = H_1^{\text{uni}}((X_1, X_2)).$$

The deterministic loss $X_3 = c$ is thus also distributed uniformly over the three participants and not only supported by participant 3 under the uniform rule.

Example 3.22. *The mean proportional rule does not satisfy the constancy property. Indeed, let $\mathbf{X}_n = (X_1, X_2, \dots, X_{n-1}, c)$, for some constant $c > 0$, and let $\mathbf{X}_{n-1} = (X_1, X_2, \dots, X_{n-1})$. Then we have that, for any $i \neq n$,*

$$H_i^{\text{prop}}(\mathbf{X}_n) = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_{n-1} + c]} (S_{n-1} + c) \neq \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_{n-1}]} S_{n-1} = H_i^{\text{prop}}(\mathbf{X}_{n-1}).$$

Example 3.23. *Neither the order statistics rule nor the multiple layer rule satisfy the constancy property.*

Examples of risk-sharing rules satisfying the constancy property will be discussed in the next sections.

Remark 3.24 (Normalization and translitivity imply constancy). One can easily prove that a risk-sharing rule $\mathbf{H}$ satisfying the normalization property (3.3) and the translitivity property (3.6), also satisfies the constancy property. Indeed, it follows from the translitivity property that for any $i \neq n$, we have that

$$\begin{aligned} H_i((X_1, X_2, \dots, X_{n-1}, c)) &= H_i((X_1, X_2, \dots, X_{n-1}, 0) + c \mathbf{1}_{n,n}) \\ &= H_i((X_1, X_2, \dots, X_{n-1}, 0)). \end{aligned}$$

Taking into account the normalization property, we then find that

$$H_i((X_1, X_2, \dots, X_{n-1}, c)) = H_i((X_1, X_2, \dots, X_{n-1})) \text{ for } i \in \{1, \dots, n-1\}.$$

A similar proof can be given for the case where $X_j = c$, for any j .

3.6 No-ripoff

Define the largest value for the loss X_i as

$$F_i^{-1}(1) = \inf\{x \in \mathbb{R} | F_i(x) = 1\},$$

where $\inf \emptyset = \infty$, by convention. It seems to be unfair to ask participants to contribute more than their maximal loss value $F_i^{-1}(1)$. This is in essence the no-ripoff requirement.

Definition 3.25 (no-ripoff property). *A risk-sharing rule $\mathbf{H}$ possesses the no-ripoff property if for any pool $\mathbf{X}_n$, one has that*

$$H_i(\mathbf{X}_n) \leq F_i^{-1}(1) \text{ for any } i = 1, 2, \dots, n. \quad (3.10)$$

Taking into account the fact that the re-allocated losses have to be non-negative, we find that the no-ripoff condition implies that any reallocated loss $H_i(\mathbf{X}_n)$ is valued in $[0, F_i^{-1}(1)]$. This intuitive requirement may nevertheless be violated when participants adopt the simple risk-sharing rules considered so far, as shown next.

Example 3.26. *The uniform risk-sharing rule does not satisfy the no-ripoff property. Considering for instance $n = 2$ and $\mathbf{X}_2 = (U, 2U)$ with U uniformly distributed over the interval $[0, 1]$, we have*

$$H_1^{\text{uni}}((U, 2U)) = \frac{3U}{2} \in [0, 1.5]$$

while $F_1^{-1}(1) = 1$.

Example 3.27. *The mean proportional risk-sharing rule does not necessarily satisfy the no-ripoff property since we might end up with $H_i^{\text{prop}}(S_n) > F_i^{-1}(1)$ when S_n becomes large. This questions the appropriateness of the mean proportional risk-sharing rule in adverse scenarios.*

Example 3.28. *Neither the order statistics rule nor the multiple layer rule satisfy the no-ripoff property.*

Examples of risk-sharing rules satisfying the no-ripoff property will be discussed in the next sections.

3.7 Actuarial fairness

Actuarial fairness of a risk-sharing rule means that on average, participants do neither gain nor lose from risk sharing, in the sense that their expected contribution (by joining the pool) is equal to their expected loss (when staying alone).

Definition 3.29 (actuarial fairness property). *A risk-sharing rule $\mathbf{H}$ satisfies the actuarial fairness property (or is said to be an actuarially fair risk-sharing rule) if for any pool $\mathbf{X}_n$, one has that*

$$\mathbb{E}[H_i(\mathbf{X}_n)] = \mathbb{E}[X_i] \text{ for any } i = 1, 2, \dots, n. \quad (3.11)$$

Example 3.30. *The uniform risk-sharing rule does not satisfy the actuarial fairness property. Considering for instance $n = 2$ and $\mathbf{X}_2 = (U, 3U)$ with U uniformly distributed over the interval $[0, 1]$, we see that*

$$H_1^{\text{uni}}((U, 3U)) = 2U$$

and

$$\mathbb{E}[H_1^{\text{uni}}((U, 3U))] = 1 \neq \frac{1}{2} = \mathbb{E}[U].$$

Example 3.31. *The mean proportional rule satisfies the actuarial fairness property since*

$$\mathbb{E}[H_i^{\text{prop}}(\mathbf{X}_n)] = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n]} \mathbb{E}[S_n] = \mathbb{E}[X_i], \text{ for any } i = 1, 2, \dots, n.$$

Example 3.32. *The order statistics rule does not satisfy the actuarial fairness property since the inequalities*

$$\mathbb{E}[H_1^{\text{ord}}(\mathbf{X}_n)] = \mathbb{E}[X_{(1)}] = \mathbb{E}[\min\{X_1, \dots, X_n\}] < \mathbb{E}[X_1]$$

and

$$\mathbb{E}[H_n^{\text{ord}}(\mathbf{X}_n)] = \mathbb{E}[X_{(n)}] = \mathbb{E}[\max\{X_1, \dots, X_n\}] > \mathbb{E}[X_n]$$

are generally true, except in some trivial cases. This means that participant 1 gains on average by joining the pool whereas participant n loses on average by doing so. Also, the multiple layer rule does not satisfy the actuarial fairness property.

3.8 Willingness to join

Usually, risk-sharing rules are set up such that each person i prefers paying $H_i(\mathbf{X})$ over paying X_i corresponding to the stand-alone position. Hence, participants are willing to join the pool. This preference could be expressed in different ways. It is important to realize that we aim at some standardization, as it is commonly the case with traditional insurance products. This is a necessary requirement for managing large insurance pools. Thus, individual preferences are only partially taken into account. First, by selecting the level of risk retention at individual level, for instance within a predefined menu of deductibles. Second, even if the proposed coverage is not optimal for each individual participant, given his or her particular preferences, it must be attractive to all members of a reasonable class (e.g. risk-averse) economic agents.

In this paper, we use the following stochastic dominance relations expressing the common preferences shared by all risk-averse economic agents in the expected utility setting for choice under risk. Given two losses X and Y , X is said to be smaller than Y in the increasing convex order, henceforth denoted by $X \preceq_{\text{ICX}} Y$ if $\mathbb{E}[u(w - X)] \geq \mathbb{E}[u(w - Y)]$ for any non-decreasing concave utility function u and wealth level w , provided the expectations exist. The increasing convex order is also called stop-loss order in actuarial science since it can be characterized by pointwise comparison of stop-loss transforms: $X \preceq_{\text{ICX}} Y \Leftrightarrow \mathbb{E}[(X - d)_+] \leq \mathbb{E}[(Y - d)_+]$ for all real d . The case where X and Y have the same expected value corresponds to the convex order $\preceq_{\text{CX}}$ which is defined as follows:

$$X \preceq_{\text{CX}} Y \Leftrightarrow X \preceq_{\text{ICX}} Y \text{ and } \mathbb{E}[X] = \mathbb{E}[Y].$$

Thus, $\preceq_{\text{CX}}$ only applies to losses with the same expected value. The term “convex” is used since $X \preceq_{\text{CX}} Y \Leftrightarrow \mathbb{E}[g(X)] \leq \mathbb{E}[g(Y)]$ for all convex functions g for which the expectations exist. The stochastic inequality $X \preceq_{\text{CX}} Y$ intuitively means that X and Y have the same “size” (as $\mathbb{E}[X] = \mathbb{E}[Y]$ holds) but that Y is “more variable” than X . For instance, the variance of Y is larger than the variance of X . For a thorough description of the convex and increasing convex orders and of their applications in insurance studies, we refer the reader to Denuit et al. (2005). A general reference about stochastic order relations is Shaked and Shanthikumar (2007).

Definition 3.33 (willingness-to-join property). *A risk-sharing rule $\mathbf{H}$ satisfies the willingness-to-join property if for any pool $\mathbf{X}_n$, one has that*

$$H_i(\mathbf{X}_n) \preceq_{\text{CX}} X_i \text{ holds for every } i = 1, 2, \dots, n. \quad (3.12)$$

Remark 3.34. Notice that replacing the convex order $\preceq_{\text{CX}}$ with the increasing convex order $\preceq_{\text{ICX}}$ in (3.12) leads to the same definition. In other words, it suffices to require $\preceq_{\text{ICX}}$ instead of the stronger $\preceq_{\text{CX}}$ in (3.12). Indeed, this is because

$$H_i(\mathbf{X}_n) \preceq_{\text{ICX}} X_i \text{ for every } i = 1, 2, \dots, n \Rightarrow \mathbb{E}[H_i(\mathbf{X}_n)] \leq \mathbb{E}[X_i] \text{ for every } i = 1, 2, \dots, n.$$

But the full allocation condition (2.2) implies that

$$\sum_{i=1}^n \mathbb{E}[H_i(\mathbf{X}_n)] = \sum_{i=1}^n \mathbb{E}[X_i]$$

so that $\mathbb{E}[H_i(\mathbf{X}_n)] = \mathbb{E}[X_i]$ must in fact hold for every $i = 1, 2, \dots, n$, and the stronger stochastic inequality $H_i(\mathbf{X}_n) \preceq_{\text{CX}} X_i$ is valid. This reasoning also shows that the willingness-to-join property for all risk-averse economic agents implies actuarial fairness.

Example 3.35. *The uniform risk-sharing rule does not satisfy the willingness-to-join property since it is not actuarially fair.*

Example 3.36. *The mean proportional rule satisfies the willingness-to-join property if*

$$H_i^{\text{prop}}(S_n) = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n]} S_n \preceq_{\text{CX}} X_i \text{ holds for every } i = 1, 2, \dots, n,$$

which is equivalent to

$$\frac{S_n}{\mathbb{E}[S_n]} \preceq_{\text{CX}} \frac{X_i}{\mathbb{E}[X_i]} \text{ for every } i = 1, 2, \dots, n.$$

The latter $\preceq_{\text{CX}}$ -inequality means that S_n and X_i must be ranked in the Lorenz order. Hence, the willingness-to-join property does not hold in general for the mean proportional rule but it does in some particular cases. We refer the reader to Section 2.4.2 in Denuit and Robert (2021c) for more details.

Example 3.37. *Neither the order statistics rule nor the multiple layer one satisfy the willingness-to-join property, because none of them is actuarially fair.*

3.9 Fair merging

Suppose that for a given vector of losses $\mathbf{X}_n$ we merge the losses X_k and X_l by replacing X_k by $X_k + X_l$ and X_l by 0, i.e. we change $\mathbf{X}_n$ into $\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})$. Then, a reasonable property is that the contribution paid by any participant different from k and l is not impacted by the merge. We will call this condition the fair-merging property. It is formally defined next.

Definition 3.38 (fair-merging property). *A risk-sharing rule $\mathbf{H}$ satisfies the fair-merging property if for any pool $\mathbf{X}_n$ and any $k \neq l$, one has that*

$$H_i(\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})) = H_i(\mathbf{X}_n) \text{ if } i \text{ is different from } k \text{ and } l. \quad (3.13)$$

Remark 3.39 (fair merging and normalization). Suppose that a risk-sharing rule $\mathbf{H}$ satisfies the fair-merging property. For any $\mathbf{X}_n$, we have that the l th component of $\mathbf{X}_n + X_l \times (\mathbf{1}_k - \mathbf{1}_l)$ is equal to 0. If $\mathbf{H}$ also satisfies the normalization property (3.3), we find that

$$H_l(\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})) = 0. \quad (3.14)$$

The full loss allocation condition (2.2) then shows that the following additivity property must hold:

$$H_k(\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})) = H_k(\mathbf{X}_n) + H_l(\mathbf{X}_n). \quad (3.15)$$

We thus see that merging X_k and X_l by replacing X_k by $X_k + X_l$ and X_l by 0 does not change the re-allocated losses (and hence, the contributions) of the participants different from k and l . The only changes in the re-allocated losses (and hence, the contributions) are such that the re-allocated loss of the k th participant equals the sum of the original re-allocated losses of participants k and l , while the re-allocated loss of participant l becomes 0. Notice that the relations (3.13), (3.14) and (3.15) can be summarized as follows: for any risk-sharing rule satisfying both the fair-merging and the normalization properties, we have

$$\mathbf{H}(\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})) = \mathbf{H}(\mathbf{X}_n) + H_l(\mathbf{X}_n)(\mathbf{1}_{k,n} - \mathbf{1}_{l,n}). \quad (3.16)$$

Example 3.40. *The uniform risk-sharing rule satisfies the fair-merging property since*

$$H_i^{\text{uni}}(\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})) = \frac{S_n}{n} = H_i^{\text{uni}}(\mathbf{X}_n)$$

for any i different from k and l . However, participants k and l still have to contribute the same amount S_n/n despite their respective losses have been merged implying that (3.15) does not hold.

Example 3.41. *The mean proportional risk-sharing rule satisfies the fair-merging property since, for any $k \neq l$,*

$$H_i^{\text{prop}}(\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})) = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n]} S_n = H_i^{\text{prop}}(\mathbf{X}_n) \text{ if } i \text{ is different from } k \text{ and } l.$$

The mean proportional risk-sharing rule also satisfies the normalization property and hence, also (3.16) holds.

Example 3.42. *Neither the order statistics risk-sharing rule nor the multiple layer rule satisfy the fair-merging property.*

Remark 3.43. Under reshuffling, (3.13) only has to hold with a given pair (k, l) to define fair merging (for instance, $k = n - 1$ and $l = n$).

3.10 Fair splitting

Assume that we split the loss X_k for participant k into the sum $X'_k + X_{n+1}$, i.e.

$$X_k = X'_k + X_{n+1} \quad (3.17)$$

where $X'_k \geq 0$ is retained by participant k and $X_{n+1} \geq 0$ is passed to a new participant $n+1$ (who can be different from or identical to participant k), i.e. we change $\mathbf{X}_n$ into

$$\left(\mathbf{X}_n + (X'_k - X_k) \times \mathbf{1}_{k,n}, X_{n+1} \right).$$

A reasonable property for a risk-sharing rule would be that the re-allocated losses (and hence, also the ex-post contributions) of all participants, excluding k and $n+1$, remain unchanged. This leads to the following definition.

Definition 3.44 (fair-splitting property). *A risk-sharing rule $\mathbf{H}$ satisfies the fair-splitting property in case for any pool $\mathbf{X}_n$, for any $k \in 1, 2, \dots, n$, and any non-negative random variables X'_k and X_{n+1} satisfying (3.17), one has that*

$$H_i(\mathbf{X}_n) = H_i\left(\left(\mathbf{X}_n + (X'_k - X_k) \times \mathbf{1}_{k,n}, X_{n+1}\right)\right) \text{ if } i \text{ is different from } k \text{ and } n+1. \quad (3.18)$$

Notice that splitting often results in perfectly dependent (or comonotonic, see below) pieces in applications to insurance, for instance $X'_k = \min\{X_k, d\}$ and $X_{n+1} = (X_k - d)_+$ for some deductible d , or $X'_k = \alpha X_k$ and $X_{n+1} = (1 - \alpha)X_k$ for some quota share $\alpha \in (0, 1)$. Here, we leave the dependence structure in the pair (X'_k, X_{n+1}) unspecified as long as (3.17) holds true.

Suppose that the risk-sharing rule $\mathbf{H}$ satisfies the fair-splitting property. For any $\mathbf{X}_n$ the full loss allocation condition (2.2) leads to

$$\sum_{i=1}^n H_i(\mathbf{X}_n) = \sum_{i=1}^{n+1} H_i\left(\left(\mathbf{X}_n + (X'_k - X_k) \times \mathbf{1}_{k,n}, X_{n+1}\right)\right). \quad (3.19)$$

Taking into account the fair-splitting property (3.18), this leads to

$$\begin{aligned} H_k(\mathbf{X}_n) &= H_k\left(\left(\mathbf{X}_n + (X'_k - X_k) \times \mathbf{1}_{k,n}, X_{n+1}\right)\right) \\ &\quad + H_{n+1}\left(\left(\mathbf{X}_n + (X'_k - X_k) \times \mathbf{1}_{k,n}, X_{n+1}\right)\right). \end{aligned} \quad (3.20)$$

From (3.18) and (3.19) we thus see that if we split the loss X_k of participant k into a loss X'_k for participant k and a loss $X_{n+1} = X_k - X'_k$ for a new participant $n+1$, then the re-allocated loss of any participant different from k remains unchanged, while the original re-allocated loss of the k th participant is equal to the sum of the newly re-allocated losses of participants k and $n+1$ after the split.

Example 3.45. *The uniform risk-sharing rule does not satisfy the fair-splitting property. Considering for instance $n = 2$ and $X_2 = X'_2 + X_3$, we see that*

$$H_1^{\text{uni}}\left(\left((X_1, X_2) + (X'_2 - X_2)\mathbf{1}_{2,2}, X_2\right)\right) = \frac{X_1 + X_2}{3} \neq \frac{X_1 + X_2}{2} = H_1^{\text{uni}}((X_1, X_2)).$$

Example 3.46. *The proportional rule satisfies the fair-splitting property since, for any $k \in 1, 2, \dots, n$, and any non-negative random variables X'_k and X_{n+1} satisfying (3.17), one has that*

$$H_i^{\text{prop}}((\mathbf{X}_n + (X'_k - X_k) \times \mathbf{1}_{k,n}, X_{n+1})) = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n]} S_n = H_i^{\text{prop}}(\mathbf{X}_n)$$

for any i different from k and $n + 1$.

Example 3.47. *Neither the order statistics risk-sharing rule nor the multiple layer rule satisfy the fair-splitting property.*

Remark 3.48. Under reshuffling, it suffices to impose (3.18) for a particular value of k , for instance $k = n$.

3.11 Comonotonicity and aggregate risk-sharing rules

Recall that the left-continuous inverse of the distribution function F_Y of a random variable Y is defined by

$$F_Y^{-1}(p) = \inf \{y \in \mathbb{R} \mid F_Y(y) \geq p\}, \quad p \in [0, 1]. \quad (3.21)$$

As previously stated, $\inf \emptyset = \infty$ by convention in (3.21). A random vector $\mathbf{Y}_n = (Y_1, \dots, Y_n)$ is said to be comonotonic if $\mathbf{Y}_n$ is distributed as $(F_{Y_1}^{-1}(U), \dots, F_{Y_n}^{-1}(U))$ for some random variable U uniformly distributed over the interval $[0, 1]$. Intuitively stated, $\mathbf{Y}_n$ is comonotonic if the increase of one of its components implies an increase of all its other components. Comonotonicity is an important dependency structure, with many applications in insurance and finance, see e.g. Dhaene et al. (2002a, b) and Deelstra et al. (2010).

In the context of risk sharing, comonotonicity of the re-allocated loss vector $\mathbf{H}(\mathbf{X}_n)$ might be a desirable property since it ensures that the interests of all participants are aligned, in the sense that they all have an interest in keeping their losses as small as possible. This leads to the following definition.

Definition 3.49 (comonotonicity). *A risk-sharing rule $\mathbf{H}$ is said to be comonotonic if for any pool $\mathbf{X}_n$ one has that $\mathbf{H}(\mathbf{X}_n)$ is a comonotonic random vector.*

Comonotonicity is also referred to as the no-sabotage condition, after Carlier and Dana (2003). It ensures that no individual contribution $H_i(\mathbf{X}_n)$ is allowed to increase more than the total losses. It turns out that comonotonic pools play an important role in the study of risk-sharing rules, in the same vein as comonotonic risks do for premium calculation principles and risk measures. The structure of comonotonic pools is further studied in Section 5.3.1.

We know from Denuit and Dhaene (2012) that $\mathbf{H}$ is comonotonic if, and only if, there exist non-decreasing functions g_i such that $H_i(\mathbf{X}_n) = H_i(S_n) = g_i(S_n)$. Comonotonic risk-sharing rules according to Definition 3.49 are thus necessarily aggregate ones.

Example 3.50. *The uniform risk-sharing rule satisfies the comonotonicity property since the random vector $(S_n/n, \dots, S_n/n)$ is obviously comonotonic.*

Example 3.51. *The mean proportional risk-sharing rule satisfies the comonotonicity property, since individual contributions are equal to the aggregate losses S_n up to positive coefficients.*

Example 3.52. *The order statistics risk-sharing rule does not satisfy the comonotonicity property, because it is not an aggregate risk-sharing rule.*

Example 3.53. *The multiple layer risk-sharing rule satisfies the comonotonicity property, since the payment in each layer is a non-decreasing function of S_n .*

3.12 Stand-alone for comonotonic losses

Within a comonotonic pool, it is reasonable to expect that each participant remains with his or her own loss since no diversification benefit can result from pooling in that case. Hence, the stand-alone risk-sharing rule appears to be reasonable in that case. These considerations lead to the following definition.

Definition 3.54 (stand-alone property for comonotonic losses). *A risk-sharing rule $\mathbf{H}$ is said to satisfy the stand-alone property for comonotonic losses if for any comonotonic pool $\mathbf{X}_n$ one has that $\mathbf{H}(\mathbf{X}_n) = \mathbf{X}_n$.*

Example 3.55. *The uniform risk-sharing rule does not satisfy the stand-alone property for comonotonic losses. Considering for instance $n = 2$ and $\mathbf{X}_2 = (U, 2U)$ with U uniformly distributed over the interval $[0, 1]$, we see that*

$$H_1^{\text{uni}}((U, 2U)) = \frac{3U}{2} \neq U.$$

Example 3.56. *The mean proportional risk-sharing rule does not necessarily satisfy the stand-alone property for comonotonic losses since X_i does not necessarily coincide with $\frac{E[X_i]}{E[S_n]}S_n$ when $\mathbf{X}_n$ is comonotonic. The same comment applies to the order statistics and the multiple layer rules which do not satisfy the stand-alone property for comonotonic losses.*

The stand-alone property for comonotonic losses will be satisfied by some of the risk-sharing rules discussed in the next sections.

4 Conditional mean risk-sharing rule

4.1 Definition

Let us recall the definition of the conditional mean risk-sharing rule introduced by Denuit and Dhaene (2012).

Definition 4.1 (conditional mean risk-sharing rule). *A risk-sharing rule $\mathbf{H}$ is the conditional mean risk-sharing rule in case for any pool $\mathbf{X}_n$, the contribution for individual i is given by*

$$H_i(\mathbf{X}_n) = H_i(S_n) = E[X_i | S_n], \quad i = 1, 2, \dots, n. \quad (4.1)$$

The conditional mean risk-sharing rule is henceforth denoted as $\mathbf{H}^{\text{cm}}$.

Under $\mathbf{H}^{\text{cm}}$, each participant must contribute the expected value of the loss brought to the pool, given the total loss S_n experienced by the pool. When $\text{Var}[S_n] < \infty$, we have

$$\mathbb{E}[(X_i - H_i^{\text{cm}}(S_n))^2] = \min_f \mathbb{E}[(X_i - f(S_n))^2],$$

where the minimum is taken over all measurable functions f such that $\text{Var}[f(S_n)] < \infty$. In words, the contribution $H_i^{\text{cm}}(S_n)$ paid by participant i is the closest to the loss X_i brought to the pool, in the sense that it minimizes the expected squared difference of the risk X_i and any measurable function $f(S_n)$ of the total loss S_n . It then follows that the net pooling effects $X_i - H_i^{\text{cm}}(S_n)$ are uncorrelated among participants.

4.2 Properties

In Denuit and Dhaene (2012), several properties of the conditional mean risk-sharing rule were proven, with special emphasis to Pareto optimality. Let us now establish the validity of the properties presented in the preceding section for this risk-sharing rule.

Proposition 4.2. *The conditional mean risk-sharing rule $\mathbf{H}^{\text{cm}}$ satisfies the reshuffling property, the normalization property, the translativity property, the positive homogeneity property, the constancy property, the no-ripoff property, the actuarial fairness property, the willingness-to-join property, the fair-merging property, the fair-splitting property, and the stand-alone property for comonotonic losses. The conditional mean risk-sharing rule does not necessarily satisfy the comonotonicity property.*

The proof of Proposition 4.2 is given in Appendix A. We can see that the conditional mean risk-sharing rule enjoys all the properties listed in Section 3, except the comonotonicity property. This property is nevertheless valid in particular cases, when the conditional expectations $s \mapsto \mathbb{E}[X_i|S_n = s]$ are all non-decreasing. Some sufficient conditions for this property to hold can be provided for pools comprising independent losses, such as the log-concavity of the distributions of the losses X_i or the large-pool case. We refer the reader to Denuit and Robert (2021c, 2021e) for more details.

Remark 4.3 (conditional mean and uniform risk-sharing rules). Obviously, the uniform risk-sharing rule $\mathbf{H}^{\text{uni}}$ is not appropriate in all situations. The typical situation where it is appropriate is exchangeability. Recall that $\mathbf{X}_n$ is called exchangeable if its joint distribution function $F_{\mathbf{X}_n}$ is symmetric in its arguments. This means that for any permutation π of $\{1, \dots, n\}$, the random vector $(X_{\pi(1)}, X_{\pi(2)}, \dots, X_{\pi(n)})$ is distributed as $\mathbf{X}_n$. In particular, if $\mathbf{X}_n$ is exchangeable then $X_1, X_2, \dots, X_n$ are identically distributed and the pool is homogeneous. If $\mathbf{X}_n$ is exchangeable then we have for any $i \neq j$ in $\{1, 2, \dots, n\}$ that

$$\mathbb{E}[X_i|S_n] = \mathbb{E}[X_j|S_n] = \frac{1}{n} \sum_{k=1}^n \mathbb{E}[X_k|S_n] = \frac{S_n}{n}.$$

This shows that

$$\mathbf{X}_n \text{ exchangeable} \Rightarrow \mathbf{H}^{\text{cm}}(\mathbf{X}_n) = \mathbf{H}^{\text{uni}}(\mathbf{X}_n). \quad (4.2)$$

We refer the reader to Charpentier et al. (2021) where the uniform risk-sharing rule is applied to independent and identically distributed losses.

5 Quantile risk-sharing rule

5.1 Definition

For any random vector $\mathbf{X}_n = (X_1, \dots, X_n)$ with respective marginal distribution functions $F_1, \dots, F_n$ and a random variable U uniformly distributed over $[0, 1]$, we define the comonotonic counterpart $\mathbf{X}_n^c$ of $\mathbf{X}_n$ as $\mathbf{X}_n^c = (F_1^{-1}(U), \dots, F_n^{-1}(U))$, with corresponding comonotonic sum S_n^c given by

$$S_n^c = \sum_{i=1}^n F_i^{-1}(U). \quad (5.1)$$

In addition to the left-continuous inverse (3.21), we will also need the right-continuous one. Recall that the right-continuous inverse of the distribution function F_Y of some random variable Y is defined by

$$F_Y^{-1+}(p) = \sup \{y \in \mathbb{R} \mid F_Y(y) \leq p\}, \quad p \in [0, 1], \quad (5.2)$$

where $\sup \emptyset = -\infty$ by convention. For any $\alpha \in [0, 1]$, we define the α -inverse $F_Y^{-1(\alpha)}$ of F_Y following Dhaene et al. (2002a) as the following convex combination of the inverses F_Y^{-1} and F_Y^{-1+} of F_Y :

$$F_Y^{-1(\alpha)}(p) = \alpha F_Y^{-1}(p) + (1 - \alpha) F_Y^{-1+}(p), \quad p \in (0, 1). \quad (5.3)$$

For any y in $(F_Y^{-1+}(0), F_Y^{-1}(1))$, defining $\alpha_y \in [0, 1]$ as

$$\alpha_y = \begin{cases} \frac{F_Y^{-1+}(F_Y(y)) - y}{F_Y^{-1+}(F_Y(y)) - F_Y^{-1}(F_Y(y))} & \text{if } F_Y^{-1+}(F_Y(y)) \neq F_Y^{-1}(F_Y(y)) \\ 1 & \text{otherwise} \end{cases} \quad (5.4)$$

we see that the identity

$$F_Y^{-1(\alpha_y)}(F_Y(y)) = y \quad (5.5)$$

holds true. By convention, we set $\alpha_y = 0$ in case $F_Y(y) = 0$ and $\alpha_y = 1$ in case $F_Y(y) = 1$. We are now ready to state the definition of the quantile risk-sharing rule.

Definition 5.1 (quantile risk-sharing rule). *A risk-sharing rule $\mathbf{H}$ is the quantile risk-sharing rule in case for any pool $\mathbf{X}_n$, the contribution for individual i is given by*

$$H_i(\mathbf{X}_n) = F_i^{-1(\alpha_{S_n})}(F_{S_n^c}(S_n)), \quad i = 1, 2, \dots, n. \quad (5.6)$$

In (5.6), S_n^c stands for the comonotonic sum defined in (5.1), while α_{S_n} satisfies

$$F_{S_n^c}^{-1(\alpha_{S_n})}(F_{S_n^c}(S_n)) = S_n. \quad (5.7)$$

The quantile risk-sharing rule is henceforth denoted as $\mathbf{H}^{\text{quant}}$.

In words, (5.6) means that every participant contributes an amount corresponding to the generalized quantile of his or her individual loss, at the same probability level. Let us

comment on the definition (5.7) for α_{S_n} . For any outcome $s \in (F_{S_n}^{-1+}(0), F_{S_n}^{-1}(1))$ of S_n , we have that $\alpha_s \in [0, 1]$ is determined from

$$F_{S_n^c}^{-1(\alpha_s)}(F_{S_n^c}(s)) = s. \quad (5.8)$$

The conventions stated before imply that

$$F_{S_n^c}^{-1(\alpha_s)}(F_{S_n^c}(s)) = \sum_{i=1}^n F_i^{-1(\alpha_s)}(F_{S_n^c}(s)) \text{ for any } s \in \mathbb{R} \quad (5.9)$$

which follows from the well-known additivity property of the generalized quantiles of a comonotonic sum; for more details, see Dhaene et al. (2002a). Taking into account (5.7), (5.9) shows that the full loss allocation condition (2.2) is fulfilled. In case the individual contributions are determined with the quantile risk-sharing rule, each member of the pool contributes the same generalized quantile of his or her own loss X_i and the probability level of the generalized quantile is determined such that the sum of the contributions constitutes the aggregate loss.

Remark 5.2. If all marginal distribution functions F_i are strictly increasing on $(F_{S_n}^{-1+}(0), F_{S_n}^{-1}(1))$ then the quantile risk-sharing rule simplifies into

$$H_i^{\text{quant}}(S_n) = F_i^{-1}(F_{S_n^c}(S_n)), \quad i = 1, 2, \dots, n. \quad (5.10)$$

Also, (5.7) reduces to $F_{S_n^c}^{-1}(F_{S_n^c}(s)) = s$.

The following simple example compares the quantile risk-sharing rule and the conditional mean risk-sharing one, showing their respective differences.

Example 5.3. Consider the pair of individual losses $\mathbf{X}_2 = (X_1, X_2)$ with $X_1 = 2U$ and $X_2 = 1 - U$ where U is uniformly distributed over the interval $[0, 1]$. The aggregate loss is given by $S_2 = 1 + U$, which takes values in $(1, 2)$. It is straightforward to verify that for any p in $[0, 1]$ we have that $F_1^{-1}(p) = 2p$ and $F_2^{-1}(p) = p$. The comonotonic modification of $\mathbf{X}_2$ is given by

$$\mathbf{X}_2^c = (F_1^{-1}(U), F_2^{-1}(U)) = (2U, U).$$

The corresponding comonotonic sum equals $S_2^c = F_1^{-1}(U) + F_2^{-1}(U) = 3U$. Its distribution function and quantile function are given by

$$F_{S_2^c}(s) = \frac{s}{3}, \quad \text{for any } s \text{ in } [0, 3]$$

and

$$F_{S_2^c}^{-1}(p) = 3p, \quad \text{for any } p \text{ in } [0, 1].$$

The conditional mean risk-sharing rule for $\mathbf{X}_2$ is given by

$$H_1^{\text{cm}}(S_2) = E[X_1 | S_2] = X_1 = 2S_2 - 2 = 2U$$

and

$$H_2^{\text{cm}}(S_2) = E[X_2 | S_2] = X_2 = 2 - S_2 = 1 - U,$$

so that $\mathbf{H}^{\text{cm}}(\mathbf{X}_2) = \mathbf{X}_2$, which means that each participant pays his or her own individual loss.

The quantile risk-sharing rule is given by

$$H_1^{\text{quant}}(S_2) = F_1^{-1}(F_{S_2^c}(S_2)) = \frac{2}{3}S_2 = \frac{2}{3}(1 + U)$$

and

$$H_2^{\text{quant}}(S_2) = F_2^{-1}(F_{S_2^c}(S_2)) = \frac{1}{3}S_2 = \frac{1}{3}(1 + U),$$

so that $\mathbf{H}^{\text{quant}}(\mathbf{X}_2) \neq \mathbf{X}_2$. The contributions are comonotonic in this case. Notice that $F_{S_2^c}(S_2)$ is uniformly distributed over the interval $(\frac{1}{3}, \frac{2}{3})$. The distribution functions

$$F_{H_1^{\text{cm}}(S_2)}(x) = \frac{x}{2} \text{ for any } x \text{ in } (0, 2),$$

and

$$F_{H_1^{\text{quant}}(S_2)}(x) = \frac{3}{2}x - 1 \text{ for any } x \text{ in } \left(\frac{2}{3}, \frac{4}{3}\right),$$

cross exactly once, with the first one having the larger right tail. Since the corresponding expected values are equal, this means that they are ordered in the convex order sense:

$$H_1^{\text{quant}}(S_2) \preceq_{\text{CX}} H_1^{\text{cm}}(S_2) = X_1 = 2U. \quad (5.11)$$

Also, $F_{H_2^{\text{cm}}(S_2)}(x) = x$ for any x in $(0, 1)$, while $F_{H_2^{\text{quant}}(S_2)}(x) = 3x - 1$ for any x in $(\frac{1}{3}, \frac{2}{3})$. Proceeding as above, we find the following convex order relation:

$$H_2^{\text{quant}}(S_2) \preceq_{\text{CX}} H_2^{\text{cm}}(S_2) = X_2 = 1 - U. \quad (5.12)$$

Assuming that both participants are risk-averse, we can conclude that each of them will prefer the quantile risk-sharing rule over the conditional mean risk-sharing rule (which in this example, comes down to bearing his or her own risk). The quantile risk-sharing rule thus improves the situation for both participants in this example.

Remark 5.4. Notice that quantiles are often not applicable at individual level to determine premiums. This is because of the high probability mass at zero exhibited by individual insurance losses, with $P[X_i = 0] = F_i(0)$ often in the range 90-99%, so that $F_i^{-1}(p) = 0$ for p up to 90-99%. Hence, if premiums charged by the insurer correspond to quantiles at probability level p , the corresponding premium amounts are 0 if p is smaller than the probability mass at zero. A comparable situation may arise with the quantile risk-sharing rule, as shown next.

Due to the special nature of the comonotonic support, see formula (C.1) in Appendix C, there is a unique point $\mathbf{x}_n$ corresponding to any outcome s of S_n^c , of the form (C.2). For any possible outcome of S_n^c , there is thus a unique point $\mathbf{x}_n$ in the connected support of S_n^c of which the components sum to s . The components x_i are precisely the values involved in the quantile risk-sharing rule. Hence, the probability that S_n^c is smaller than, or equal to s is equal to the value of the joint distribution function of $\mathbf{X}_n^c$ at that point, and we know from Dhaene et al. (2002a) that the joint distribution function of a comonotonic random vector

is equal to the minimum of the respective marginal distribution functions. This allows us to write

$$F_{S_n^c}(s) = \min \left\{ F_1(F_1^{-1(\alpha_s)}(F_{S_n^c}(s))), \dots, F_n(F_n^{-1(\alpha_s)}(F_{S_n^c}(s))) \right\}. \quad (5.13)$$

Now, consider losses X_i obeying zero-augmented distributions, as those encountered in the majority of insurance applications (compound Poisson distributions with continuous severities, or zero-augmented Gamma or LogNormal distributions, for instance). This means that $F_i(0) > 0$ and F_i is continuously increasing over $(0, \infty)$. Then, formula (5.13) shows that the identity $F_{S_n^c}(0) = \min\{F_1(0), \dots, F_n(0)\}$ is valid. Once the value of S_n is known to be equal to s , two situations may occur. Either $F_{S_n^c}(s) > \max\{F_1(0), \dots, F_n(0)\}$ and every participant contributes to the total loss, that is, $H_i^{\text{quant}}(s) > 0$ for all i . Or $F_{S_n^c}(s) \leq \max\{F_1(0), \dots, F_n(0)\}$ and participants with larger probabilities masses at zero, or no-claim probabilities, i.e. those participants i for which $F_{S_n^c}(s) \leq F_i(0)$ do not have to contribute ex post. Assuming that participants are numbered so that $F_1(0) < F_2(0) < \dots < F_n(0)$ and that s is such the $F_j(0) < F_{S_n^c}(s) \leq F_{j+1}(0)$, this implies that participants $j+1, \dots, n$ do not have to contribute to S_n . This may lead to problematic situations in P2P insurance schemes since it is reasonable to expect that all participants putting the pool at risk must contribute to S_n ex post. Assume for instance that the realizations of losses $X_1, \dots, X_{n-1}$ are all 0 but that $X_n = x_n > 0$. If x_n is such that $F_1(0) < F_{S_n^c}(x_n) < F_2(0)$ then participant 1 will have to pay x_n (alone) while participant n is the only one having caused some loss within the pool. This may cause moral hazard issues.

If no-claim probabilities are all equal then the problem disappears. This is the case when $F_i(0)$ are all zero, or can be considered as being negligible (for instance when $X_1, \dots, X_n$ correspond to business lines or insurance portfolios). The problem also disappears when the number of participants to the pool becomes sufficiently large, as shown next. The probability that every participant contributes to the total loss is given by

$$\mathbb{P}[H_i^{\text{quant}}(S_n) > 0 \text{ for all } i] = \mathbb{P}[F_{S_n^c}(S_n) > \max\{F_1(0), \dots, F_n(0)\}].$$

If participants are numbered so that $F_1(0) < F_2(0) < \dots < F_n(0)$ then this probability is also equal to

$$\mathbb{P}[S_n > F_{S_n^c}^{-1}(F_n(0))] = \mathbb{P}\left[S_n > \sum_{j=1}^n F_j^{-1}(F_n(0))\right].$$

Let us now consider large pools, i.e., the number n of participants becomes larger and larger, and assume that, for all $i = 1, \dots, n$, the inequality $F_i(0) \leq \eta$ holds for some $0 < \eta < 1$. If for all $i = 1, \dots, n$ and for some $0 < \varepsilon < 1$,

$$F_i^{-1}(\eta) \leq (1 - \varepsilon) \mathbb{E}[X_i],$$

then, provided a law of large numbers applies to individual losses X_i , the probability that every participant contributes to the total loss under the quantile risk-sharing rule tends to 1 as n tends to infinity.

Remark 5.5 (quantile and uniform risk-sharing rules). If $X_1, X_2, \dots, X_n$ are identically distributed with common distribution function F then the full allocation condition gives

$S_n = nF^{-1}(\alpha_{S_n}) (F_{S_n^c} (S_n))$. This shows that

$$H_i^{\text{quant}}(\mathbf{X}_n) = H_i^{\text{uni}}(S_n) = \frac{S_n}{n}$$

whatever the dependence structure of individual losses X_i . More generally, the quantile risk-sharing rule does not take into account the dependency structure between the individual losses.

Example 5.6 (scale proportional risk-sharing rule). *If $F_i(x) = F(x/\sigma_i)$ for some distribution function F and some particular scale factors $\sigma_i > 0$, then*

$$H_i^{\text{quant}}(\mathbf{X}_n) = \sigma_i F^{-1}(\alpha_{S_n}) (F_{S_n^c} (S_n)) \text{ for } i = 1, \dots, n.$$

The full allocation condition then gives

$$F^{-1}(\alpha_{S_n}) (F_{S_n^c} (S_n)) = \frac{S_n}{\sum_{j=1}^n \sigma_j}$$

which allows us to conclude that

$$H_i^{\text{quant}}(\mathbf{X}_n) = \frac{\sigma_i}{\sum_{j=1}^n \sigma_j} S_n$$

whatever the dependence structure of the individual losses X_i . The quantile risk-sharing rule then coincides with the scale proportional risk-sharing rule $\mathbf{H}^{\text{scale}}$ where participants agree to share the total loss S_n according to ratios based on their respective scale parameter, divided by the sum of all scale parameters.

5.2 Properties

Let us now establish the validity of the properties presented in the Section 3 for the quantile risk-sharing rule.

Proposition 5.7. *The quantile risk-sharing rule $\mathbf{H}^{\text{quant}}$ satisfies the reshuffling property, the normalization property, the translativity property, the positive homogeneity property, the constancy property, the no-ripoff property, the comonotonic property, and the stand-alone property for comonotonic losses. The quantile risk-sharing rule does not necessarily satisfy the actuarial fairness property, the willingness-to-join property, the fair-merging property, and the fair-splitting property.*

The proof of Proposition 5.7 is given in Appendix B.

Remark 5.8. Notice that the quantile risk-sharing rule $\mathbf{H}^{\text{quant}}$ satisfies the fair-merging property when X_k and X_l are comonotonic since the identity $F_{X_k+X_l}^{-1}(\alpha)(p) = F_{X_l}^{-1}(\alpha)(p) + F_{X_k}^{-1}(\alpha)(p)$ holds true for all probability levels p and all α in this case, and because of full allocation. Similarly, the quantile risk-sharing rule satisfies the fair-splitting property in the particular case where X'_k and X_{n+1} are comonotonic.

5.3 Links between conditional mean and quantile risk-sharing rules

5.3.1 Comonotonic pools

Comonotonic pools play an important role in the study of risk-sharing rules. Within comonotonic pools, every individual loss is in fact an increasing function of the aggregate loss of the entire pool, as shown next.

Proposition 5.9. *The pool $\mathbf{X}_n$ is comonotonic if, and only if,*

$$\mathbf{X}_n = (h_1(S_n), h_2(S_n), \dots, h_n(S_n)) \quad (5.14)$$

with the functions $h_i, i = 1, 2, \dots, n$, given by

$$h_i(s) = F_i^{-1(\alpha_s)}(F_{S_n}(s)), \quad \text{for any } s \in \mathbb{R}, \quad (5.15)$$

where α_s is defined by (5.8).

The proof of the new characterization of comonotonicity in Proposition 5.9 is given in Appendix C.

Consider a comonotonic pool $\mathbf{X}_n$. From equations (5.14) and (5.15) in Proposition 5.9, we find that

$$(E[X_1 | S_n], E[X_2 | S_n], \dots, E[X_n | S_n]) = (h_1(S_n), h_2(S_n), \dots, h_n(S_n)) = \mathbf{X}_n.$$

Conversely, if

$$\mathbf{X}_n = (E[X_1 | S_n], E[X_2 | S_n], \dots, E[X_n | S_n]) \quad (5.16)$$

holds with $E[X_i | S_n]$ non-decreasing in S_n for all i then it follows that $\mathbf{X}_n$ is comonotonic. This leads to the following new characterization of comonotonic pools in terms of those left unchanged by the conditional mean risk-sharing rule.

Proposition 5.10. *The pool $\mathbf{X}_n$ is comonotonic if, and only if, it admits the representation (5.16) where the conditional expectations $E[X_i | S_n], i = 1, 2, \dots, n$, are non-decreasing functions of S_n .*

Proposition 5.10 gives a useful characterization of comonotonicity in terms of the conditional expectations defining the conditional mean risk-sharing rule. Propositions 5.9 and 5.10 clearly show that a pool is comonotonic if, and only if, the individual losses it comprises can be considered as increasing functions of the aggregate loss, meaning in fact that the randomness of any individual loss is only caused by the randomness of the aggregate loss.

Propositions 5.9 and 5.10 can be summarized as follows.

Proposition 5.11. *The following statements are equivalent:*

- (1) *The pool $\mathbf{X}_n$ is comonotonic.*
- (2) $\mathbf{X}_n = \mathbf{H}^{\text{quant}}(\mathbf{X}_n)$.
- (3) $\mathbf{X}_n = \mathbf{H}^{\text{cm}}(\mathbf{X}_n)$ with all $H_i^{\text{cm}}(\mathbf{X}_n)$ non-decreasing functions of S_n .

5.3.2 Marginal VaR

The risk-sharing rules $\mathbf{H}^{\text{cm}}$ and $\mathbf{H}^{\text{quant}}$ can both be obtained from marginal VaR, as shown next. For $\boldsymbol{\lambda} \in \mathbb{R}_+^n$, let $S_n(\boldsymbol{\lambda}) = \sum_{i=1}^n \lambda_i X_i$ and $S_n^c(\boldsymbol{\lambda}) = \sum_{i=1}^n \lambda_i X_i^c$. Assume that $\mathbf{X}_n$ has a strictly positive density function. It is well-known that $F_{S_n(\boldsymbol{\lambda})}^{-1}(\epsilon)$ and $F_{S_n^c(\boldsymbol{\lambda})}^{-1}(\epsilon)$ are positive-homogeneous function of order 1 with respect to $\boldsymbol{\lambda}$. By Euler's rule, we deduce

$$F_{S_n(\boldsymbol{\lambda})}^{-1}(\epsilon) = \sum_{i=1}^n \lambda_i \frac{\partial F_{S_n(\boldsymbol{\lambda})}^{-1}(\epsilon)}{\partial \lambda_i} \quad \text{and} \quad F_{S_n^c(\boldsymbol{\lambda})}^{-1}(\epsilon) = \sum_{i=1}^n \lambda_i \frac{\partial F_{S_n^c(\boldsymbol{\lambda})}^{-1}(\epsilon)}{\partial \lambda_i}.$$

We then have

$$\frac{\partial F_{S_n(\boldsymbol{\lambda})}^{-1}(\epsilon)}{\partial \lambda_i} = \mathbb{E}[X_i | S_n(\boldsymbol{\lambda}) = F_{S_n(\boldsymbol{\lambda})}^{-1}(\epsilon)] \quad \text{and} \quad \frac{\partial F_{S_n^c(\boldsymbol{\lambda})}^{-1}(\epsilon)}{\partial \lambda_i} = F_i^{-1}(\epsilon).$$

Hence, we see that

$$\begin{aligned} \left. \frac{\partial F_{S_n(\boldsymbol{\lambda})}^{-1}(\epsilon)}{\partial \lambda_i} \right|_{\boldsymbol{\lambda}=\mathbf{1}, \epsilon=F_{S_n}^{-1}(S_n)} &= H_i^{\text{cm}}(\mathbf{X}_n) \\ \left. \frac{\partial F_{S_n^c(\boldsymbol{\lambda})}^{-1}(\epsilon)}{\partial \lambda_i} \right|_{\epsilon=F_{S_n^c}^{-1}(S_n)} &= H_i^{\text{quant}}(\mathbf{X}_n). \end{aligned}$$

6 Generalized conditional mean risk-sharing rules

6.1 Change of distribution

It is possible to offer an additional degree of freedom to the group of participants by allowing them to base the risk-sharing rule on another distribution for $\mathbf{X}_n$ they agree about, leaving the total loss S_n to be shared unchanged. Thus, all participants agree to replace the actual (distribution of) loss random vector $\mathbf{X}_n$ with (the distribution of) another random vector for the sake of risk sharing. The latter is called the modification of $\mathbf{X}_n$ and henceforth denoted as $\mathbf{M}(\mathbf{X}_n) = (M_1(\mathbf{X}_n), \dots, M_n(\mathbf{X}_n))$. Possible reasons why participants choose a modification of the pool to share could be that the joint distribution function of the original pool is only partly known, or they do not want to take into account the dependency structure (maybe because it is unknown). The comonotonic version $\mathbf{X}_n^c$ is an example of such a modified loss random vector that only depends on the marginal distribution functions of the original pool. This suggests to adopt the following definition.

Definition 6.1 (generalized conditional mean risk-sharing rule). *A risk-sharing rule $\mathbf{H}$ is a generalized conditional mean risk-sharing rule in case for any pool $\mathbf{X}_n$, there is a modified loss random vector $\mathbf{M}(\mathbf{X}_n)$ with sum $T_n = \sum_{i=1}^n M_i(\mathbf{X}_n)$, such that the ex-post contribution of individual i is given by*

$$H_i(s) = \mathbb{E}[M_i(\mathbf{X}_n) | T_n = s], \quad i = 1, 2, \dots, n, \quad (6.1)$$

where s is the realization of S_n . The generalized conditional mean risk-sharing rule for a pool $\mathbf{X}_n$ based on modified losses $\mathbf{M}(\mathbf{X}_n)$ is henceforth denoted as $\mathbf{H}^{\text{gcm}}(\mathbf{X}_n; \mathbf{M}(\mathbf{X}_n))$.

Some compatibility conditions are needed so that conditional expectation in (6.1) is well defined and (6.1) defines a risk-sharing rule. Henceforth, we always assume that the modified loss random vector $\mathbf{M}(\mathbf{X}_n)$ is such that any outcome of S_n is also a possible outcome for T_n . Stated more formally, the support for S_n (defined as the set of all the possible values for S_n) has to be included in the support of T_n so that the conditioning makes sense. This is generally satisfied in applications to insurance where the supports of S_n and T_n are often $[0, \infty)$. Henceforth, we tacitly assume that the compatibility condition is fulfilled.

By a suitable choice of $\mathbf{M}(\mathbf{X}_n)$, we can then relate many risk-sharing rules to the conditional mean risk-sharing one. For instance, we know from implication (4.2) that the uniform risk-sharing rule is equivalent to the conditional mean risk-sharing rule with $\mathbf{M}(\mathbf{X}_n)$ exchangeable. This is the approach proposed by Skogh and Wu (2005) who argue that agents presuming that they are faced with exchangeable risks can share them mutually beneficially.

Example 6.2 (Mean proportional risk-sharing rule as generalized conditional mean risk-sharing rule). *The mean proportional risk-sharing rule appears to be a generalized conditional mean risk-sharing rule by choosing for $\mathbf{M}(\mathbf{X}_n)$ a positive random vector with an infinitely divisible distribution whose component means are the same as $\mathbf{X}_n$, as shown by Denuit and Robert (2021g).*

6.2 Quantile risk-sharing rule as generalized conditional mean risk-sharing rule

In this section, we consider the generalized conditional mean risk-sharing rule, where for any pool $\mathbf{X}_n$, we set $\mathbf{M}(\mathbf{X}_n)$ equal to its comonotonic version $\mathbf{X}_n^c = (F_1^{-1}(U), \dots, F_n^{-1}(U))$, with U uniformly distributed over the interval $[0, 1]$. This leads to the following definition.

Definition 6.3 (comonotonic conditional mean risk-sharing rule). *A risk-sharing rule $\mathbf{H}$ is the comonotonic conditional mean risk-sharing rule in case for any pool $\mathbf{X}_n$, the contribution for individual i is well-defined and given by*

$$H_i(s) = \mathbb{E}[X_i^c \mid S_n^c = s], \quad i = 1, 2, \dots, n, \quad (6.2)$$

where $S_n^c = \sum_{i=1}^n X_i^c$ and s is the realization of the pool's aggregate loss S_n . The comonotonic conditional mean risk-sharing rule is henceforth denoted as $\mathbf{H}^{\text{ccm}}$.

The risk-sharing rule $\mathbf{H}^{\text{ccm}}$ is thus obtained from $\mathbf{H}^{\text{ccm}}(\mathbf{X}_n) = \mathbf{H}^{\text{gcm}}(\mathbf{X}_n; \mathbf{X}_n^c)$, where S_n^c corresponds to T_n in (6.1).

Notice that even with the comonotonic version of $\mathbf{X}_n$, some compatibility conditions are needed to properly define the generalized conditional mean risk-sharing rule. Consider for instance $n = 2$ with X_1 and X_2 independent and uniformly distributed over the union of intervals $[0, 1] \cup [2, 3]$. The support of S_2 is $[0, 6]$ whereas the support of S_2^c is $[0, 2] \cup [4, 6]$. If the outcome of S_2 is 3 then the conditional expectation (6.2) is not defined. This kind of problem does not happen with losses having strictly increasing distribution functions over the interval $[F_i^{-1+}(0), F_i^{-1}(1)]$. Another simple sufficient condition is that the support of all losses X_i is the set of non-negative real values. The risk-sharing rule $\mathbf{H}^{\text{ccm}}$ is thus applicable in insurance studies where losses generally obey zero-augmented distributions (as defined in Remark 5.4).

Let us now investigate the relation between the risk-sharing rules $\mathbf{H}^{\text{quant}}$ and $\mathbf{H}^{\text{ccm}}$. From the definitions of $\mathbf{H}^{\text{quant}}$ and $\mathbf{H}^{\text{ccm}}$, together with Proposition 5.11, we see that for any pool $\mathbf{X}_n$ with aggregate loss S_n ,

$$H_i^{\text{ccm}}(s) = \mathbb{E}[X_i^c \mid S_n^c = s] = F_i^{-1(\alpha_s)}(F_{S_n^c}(s)) = H_i^{\text{quant}}(s),$$

for any $i = 1, 2, \dots, n$. This leads to the following result.

Proposition 6.4. *For any pool $\mathbf{X}_n$ for which the comonotonic conditional mean risk-sharing rule is well-defined, one has that $\mathbf{H}^{\text{quant}}(\mathbf{X}_n) = \mathbf{H}^{\text{ccm}}(\mathbf{X}_n)$.*

In the following example, we compare the conditional mean risk-sharing rule, the comonotonic conditional mean risk-sharing rule, and the quantile risk-sharing rule in a simple case.

Example 6.5 (Continuation of Example 5.3). *Consider again the pair of individual losses $\mathbf{X}_2 = (X_1, X_2)$ with $X_1 = 2U$ and $X_2 = 1 - U$. The comonotonic conditional mean risk-sharing rule $\mathbf{H}^{\text{ccm}}$ defined in (6.2) applied to $\mathbf{X}_2$ gives rise to*

$$H_1^{\text{ccm}}(s) = \mathbb{E}[X_1^c \mid S_2^c = s] = \frac{2}{3}s$$

and

$$H_2^{\text{ccm}}(s) = \mathbb{E}[X_2^c \mid S_2^c = s] = \frac{1}{3}s,$$

which means that

$$H_1^{\text{ccm}}(S_2) = \frac{2}{3}S_2 = \frac{2}{3}(1 + U) \neq X_1$$

and

$$H_2^{\text{ccm}}(S_2) = \frac{1}{3}S_2 = \frac{1}{3}(1 + U) \neq X_2.$$

In this example, the comonotonic conditional mean risk-sharing rule leads to comonotonic contributions. Summarizing what has been obtained in this example and Example 5.3 for the pool $\mathbf{X}_2 = (X_1, X_2) = (2U, 1 - U)$, we have that

$$\mathbf{H}^{\text{quant}}(\mathbf{X}_2) = \mathbf{H}^{\text{ccm}}(\mathbf{X}_2) = \left(\frac{2}{3}(1 + U), \frac{1}{3}(1 + U) \right)$$

while

$$\mathbf{H}^{\text{cm}}(\mathbf{X}_2) = \mathbf{X}_2 = (2U, 1 - U),$$

which is in line with Proposition 6.4.

6.3 Generalized proportional rules as generalized conditional mean risk-sharing rules

The change of distribution can also operate on the random vector of proportions. To this end, notice that the conditional mean risk-sharing rule can be rewritten as

$$H_i^{\text{cm}}(S_n) = \mathbb{E}[X_i \mid S_n] = S_n \mathbb{E}[\Theta_i(S_n)]$$

where the vector of proportions $\Theta_n(s)$ is defined as

$$\Theta_n(s) = \left(\frac{X_1}{S_n}, \dots, \frac{X_n}{S_n} \right) \Big| S_n = s.$$

An extension of the conditional mean risk-sharing rule can then be obtained by replacing $(\Theta_n(s))_{s>0}$ with a modified vector of proportions $(\mathbf{M}(\Theta_n(s)))_{s>0}$, but leaving the distribution of S_n unchanged. This defines the generalized conditional mean risk-sharing rule $H^{\text{gcm}}(\cdot; \mathbf{M}(\Theta_n))$ as

$$H_i^{\text{gcm}}(S_n; \mathbf{M}(\Theta_n)) = S_n \mathbb{E}[M_i(\Theta_n(S_n)) | S_n]$$

where $\mathbf{M}(\Theta_n)$ is the modified vector of proportions that may be correlated with S_n . An alternative to replacing $\mathbf{X}_n$ with $\mathbf{M}(\mathbf{X}_n)$ thus consists in adopting another distribution for the random vector of proportions Θ_n .

Example 6.6. Consider absolutely continuous individual losses X_i with marginal distribution functions F_i , $i = 1, \dots, n$. Assume that $\mathbf{M}(\Theta_n(s))$ obeys the Dirichlet distribution with parameter $\alpha(s) = (\alpha_1(s; F_1), \alpha_2(s; F_2), \dots, \alpha_n(s; F_n))$ with $\alpha_i(s; F_i) > 0$ for $i = 1, \dots, n$. Then

$$\mathbb{E}[M_i(\Theta_n(s))] = \frac{\alpha_i(s; F_i)}{\sum_{j=1}^n \alpha_j(s; F_j)}.$$

Total losses S_n are thus distributed among participants according to the proportions $\alpha_i(S_n; F_i) / \sum_{j=1}^n \alpha_j(S_n; F_j)$. In particular, if $\alpha_i(s, F_i) = \mathbb{E}[X_i]$ then

$$H_i^{\text{gcm}}(S_n; \mathbf{M}(\Theta_n)) = \frac{\mathbb{E}[X_i]}{\mathbb{E}[S_n]} S_n = H_i^{\text{prop}}(S_n)$$

and we recover the mean proportional risk-sharing rule.

7 Pooled deductible

The pure P2P insurance approach described in the preceding sections requires a high level of trust since the contributions to be paid ex post remain unknown until the end of the period, and some participants may be unable, or unwilling to pay their contributions at that time. Also, unless participants are ready to pay expensive contributions, the risk-bearing capacity of the community is limited. This is why an alternative approach may be interesting.

In this section, we extend the system proposed by Denuit (2020) under the conditional mean risk-sharing rule and the no-sabotage condition to any comonotonic rule. It is based on a pooled deductible of amount d where the lower layer $(0, d)$ of S_n is retained by the community whereas the upper layer (d, ∞) is transferred to an insurer. By partnering with an established insurance company, the community benefits from the claim settlement expertise developed by the insurer and its risk-bearing capacity. Each participant brings a deposit ex ante, replacing the insurance premium, with the guarantee that the final amount due never exceeds this down payment. The cash-back or give-back mechanism then operates ex post to distribute the surplus among members of the community. If members are offered the choice

among different causes they care about, it is important to allocate the surplus to each of them, individually. This system is precisely described hereafter.

Consider a risk sharing rule $\mathbf{H}$ satisfying the fair-splitting, the fair-merging, and the willingness-to-join properties. This ensures that the system is attractive to risk-averse individuals and that there is no incentive in artificially splitting or merging individual losses. Also, assume that $\mathbf{H}$ is comonotonic (and is thus an aggregate risk-sharing rule). Aggregate loss S_n is the sum of the comonotonic random variables $H_i(S_n)$ by the full-allocation property (2.2). Corollary 7.2.1 in Dhaene and Linders (2019) then shows that there exist $d_1, \dots, d_n$ for any $d \in (F_{S_n}^{-1+}(0), F_{S_n}^{-1}(1))$ such that $\sum_{i=1}^n d_i = d$ and the identities

$$(d - S_n)_+ = \sum_{i=1}^n (d_i - H_i(S_n))_+ \text{ and } (S_n - d)_+ = \sum_{i=1}^n (H_i(S_n) - d_i)_+ \quad (7.1)$$

both hold true with

$$d_i = F_{H_i(S_n)}^{-1(\alpha_d)}(F_{S_n}(d)), \quad i = 1, 2, \dots, n, \quad (7.2)$$

where α_d is given by (5.4).

Identities (7.1) allow us to compute the respective contributions for each participant to the retained loss $\min\{S_n, d\}$ since

$$\begin{aligned} \min\{S_n, d\} &= d - (d - S_n)_+ \\ &= \sum_{i=1}^n \left(d_i - (d_i - H_i(S_n))_+ \right) \\ &= \sum_{i=1}^n \min\{H_i(S_n), d_i\}. \end{aligned} \quad (7.3)$$

The loss $\min\{S_n, d\}$ retained by the pool is thus distributed among its members according to formula (7.3) and the contribution paid by participant i for the lower layer $(0, d)$ is equal to $\min\{H_i(S_n), d_i\}$ where d_i is obtained from (7.2).

The deposit π_i to be paid ex ante by participant i is decomposed into

$$\pi_i = \pi_i^{\text{P2P}} + \pi_i^{\text{SL}}$$

supplemented with expenses, where π_i^{P2P} is used to cover the lower layer shared within the P2P community and π_i^{SL} is the contribution to the price of the stop-loss protection for the upper layer (d, ∞) . To ensure that the community has enough financial resources to cover the lower layer, we must have $d = \sum_{i=1}^n \pi_i^{\text{P2P}}$ and we take $\pi_i^{\text{P2P}} = d_i$. The surplus that can be shared among participants or given to a charity is

$$B_{\text{P2P}} = (d - S_n)_+ = \sum_{i=1}^n (d_i - H_i(S_n))_+$$

by virtue of (7.1). If the community decides to distribute B_{P2P} among participants then the cash-back $B_i = (d_i - H_i(S_n))_+$ is paid to participant i . In case participants can select the cause they care about then B_i is the amount of give-back in favor of the charity elected by participant i .

Let us now explain how to allocate the stop-loss premium for the upper layer (d, ∞) among participants. To this end, assume that the price of the stop-loss protection is of the form

$$\pi_{\text{SL}} = (1 + \theta_{\text{SL}})E[(S_n - d)_+]$$

where θ_{SL} is the loading applied by the insurer covering the upper layer (d, ∞) . Identities (7.1) then provide us with the appropriate allocation rule: participant i pays

$$\pi_i^{\text{SL}} = (1 + \theta_{\text{SL}})E[(H_i(S_n) - d_i)_+]$$

for the transfer of the upper layer (d, ∞) . These amounts sum to π_{SL} .

Since the insurer charges a loading in addition to the pure premium for the stop-loss protection, the system cannot be fair as a whole. If the risk-sharing rule $\mathbf{H}$ satisfies the actuarial fairness property then the pooled deductible system is fair if we exclude this loading: the expected amount of contribution paid by participant i , taking the cash-back/give-back mechanism into account is equal to the expected loss $E[X_i]$ brought to the pool. This can be established following the same reasoning as the one in Denuit (2020) for the conditional mean risk-sharing rule.

8 Some non-aggregate risk-sharing rules

In the previous sections, we mainly presented and discussed aggregate risk-sharing rules. Let us now introduce several risk-sharing rules that do not depend only on the sum S_n .

8.1 Convex combinations

Participants could combine several risk-sharing rules since any convex combination of risk-sharing rules is itself a risk-sharing rule. This is precisely stated next.

Property 8.1. *If $\mathbf{H}_1$ and $\mathbf{H}_2$ are risk-sharing rules, then, for any $\delta \in [0, 1]$, $\delta\mathbf{H}_1 + (1 - \delta)\mathbf{H}_2$ is a risk-sharing rule.*

Combining the stand-alone rule with an aggregate risk-sharing rule then produces a rule depending on $\mathbf{X}_n$, not only on S_n .

Example 8.2. *A convex combination of the stand-alone and the conditional mean risk-sharing rule produces*

$$H_i(\mathbf{X}_n) = \delta X_i + (1 - \delta) E[X_i | S_n].$$

Under exchangeable losses (or replacing the conditional mean risk-sharing rule with the uniform one), we obtain

$$H_i(\mathbf{X}_n) = \delta X_i + (1 - \delta) \frac{S_n}{n}$$

which resembles a credibility premium. The latter risk-sharing rule has been proposed by Charpentier et al. (2021).

8.2 Network-based conditional mean risk-sharing rule

Another way to design new risk sharing rules consists in locating participants on a network to describe the links existing between them. Network structures are particularly effective in the context of risk sharing within P2P insurance communities, as demonstrated by Charpentier et al. (2021) and Denuit and Robert (2021h). Participants are thus organized into teams and the risk-sharing rule primarily operates within teams.

For participant i , we define the subset $\mathcal{C}(i)$ of participants that are connected with him or her, with associated weights $\{w_{ii}, w_{ij} : j \in \mathcal{C}(i)\}$ such that $w_{ii} > 0$, $w_{ij} > 0$ for $j \in \mathcal{C}(i)$, $w_{ii} + \sum_{j \in \mathcal{C}(i)} w_{ij} = 1$. The loss X_i is split into $\#\mathcal{C}(i) + 1$ parts. For $j \in \mathcal{C}(i)$, the parts $w_{ij}X_i$ will be considered for the sub-pool attached to participant j . The part $w_{ii}X_i$ will be considered for his or her own sub-pool.

Let

$$S_{\mathbf{w},i} = w_{ii}X_i + \sum_{j \in \mathcal{C}(i)} w_{ji}X_j$$

be the aggregated losses considered for participant i 's conditional mean risk-sharing rule. Let us define respectively the contribution $H_{ii}(S_{\mathbf{w},i}) = E[w_{ii}X_i | S_{\mathbf{w},i}]$ of participant i to his or her sub-pool and the contribution $H_{ij}(S_{\mathbf{w},i}) = E[w_{ji}X_j | S_{\mathbf{w},i}]$ of participant j to the sub-pool of participant i . The contribution of participant i to the global pool is then given by

$$H_i(\mathbf{X}_n) = H_{ii}(S_{\mathbf{w},i}) + \sum_{j \in \mathcal{C}(i)} H_{ji}(S_{\mathbf{w},j}).$$

These contributions satisfy the full loss allocation condition; see Appendix D for a proof.

8.3 Non-individualized losses

Sometimes, it is not possible, or not desirable, to attribute a loss impacting the pool to a given participant. For instance, members of the pool can be large industrial plants polluting the environment and damages cannot be individualized, resulting from their combined action. Participants could then be willing to allocate the losses according to the chance they would have produced them. In this way, heterogeneity is accounted for since participants bringing comparatively "larger" losses must assume a larger share of the total loss.

Assume that the losses are absolutely continuous with respective probability density function f_i for participant i . Adopting a collective point of view, losses are just realizations from the mixture density

$$f(x) = \frac{1}{n} \sum_{i=1}^n f_i(x).$$

The probability that a realization x of a random variable X with probability density function f has been produced by the i th component f_i of the mixture is $\frac{f_i(x)}{\sum_{j=1}^n f_j(x)}$. For each observed loss x_k , we compute the probability

$$\beta_{ik} = \frac{f_i(x_k)}{\sum_{j=1}^n f_j(x_k)}$$

that it has been produced by participant i . Clearly, the proportions β_{ik} sum to 1.

Having recorded losses $x_1, \dots, x_m$ where m may differ from the number of participants (here, the pool is seen as a collective), participant i must then contribute ex post the amount

$$H_i^{\text{coll}}(\mathbf{x}_m) = \sum_{k=1}^m \beta_{ik} x_k = \sum_{k=1}^m \frac{f_i(x_k)}{\sum_{j=1}^n f_j(x_k)} x_k$$

to the total loss. As it was the case with the quantile risk-sharing rule, contributions only depend on the marginal distribution of the losses, not on their dependence structure. It is easy to see that

$$\sum_{i=1}^n H_i^{\text{coll}}(\mathbf{x}_m) = \sum_{k=1}^m x_k.$$

The risk-sharing rule $\mathbf{H}^{\text{coll}}$ is actuarially fair, as shown in Appendix E. In the homogeneous case, $f_1 = \dots = f_n$, we recover the uniform risk-sharing rule, whatever the dependency structure of individual losses (not only under exchangeability).

Remark 8.3. The formulas still apply with $m = n$, that is, when we can attribute the loss X_i to participant i . Moving to the zero augmented case with $P[X_i = 0] > 0$, the same formula applies with the probability density function f_i of X_i over $(0, \infty)$ since the zero losses can be neglected in the preceding sums, so that we end up with

$$H_i^{\text{coll}}(\mathbf{x}_n) = \sum_{k|x_k>0} \beta_{ik} x_k = \sum_{k|x_k>0} \frac{f_i(x_k)}{\sum_{j=1}^n f_j(x_k)} x_k.$$

8.4 Claim-only conditional mean risk-sharing rule

We could operate the sharing only among individuals who suffer a positive loss, letting the claim-free ones out of the exchange. This is particularly useful to distribute a given amount of resources among the individuals in need as it is the case in contingent risk funds, as explained next.

Define

$$I_i = \begin{cases} 1 & \text{if } X_i > 0, \\ 0 & \text{otherwise.} \end{cases}$$

Also, denote as $\mathbf{I}_n$ the random vector $(I_1, \dots, I_n)$. To restrict the sharing to claimants, we can use the modified conditional mean risk-sharing rule defined as $E[X_i | S_n, \mathbf{I}_n]$. Since $I_i = 0$ implies $E[X_i | S_n, \mathbf{I}_n] = 0$ claim-free participants do not bear any losses. The claim-only conditional mean risk-sharing rule $\mathbf{H}^{\text{cm},+}$ is defined as

$$H_i^{\text{cm},+}(\mathbf{X}_n) = E[X_i | S_n, \mathbf{I}_n], \quad i = 1, 2, \dots, n. \quad (8.1)$$

Obviously, $\mathbf{H}^{\text{cm},+}$ satisfies the full allocation condition.

Remark 8.4. In case $\mathbf{X}_n$ is exchangeable, the claim-only conditional mean risk sharing rule reduces to a uniform allocation among claimants, that is,

$$\mathbf{X}_n \text{ exchangeable} \Rightarrow H_i^{\text{cm},+}(\mathbf{X}_n) = I_i \frac{S_n}{\sum_{j=1}^n I_j}$$

with the understanding that $H_i^{\text{cm},+}(\mathbf{X}_n) = 0$ when $\sum_{j=1}^n I_j = 0$.

The rule $\mathbf{H}^{\text{cm},+}$ appears to be useful within contingent risk funds where a fixed budget b is distributed among participants who suffer from losses. Participant i then receives the share $E[X_i|S_n, \mathbf{I}_n]/S_n$ of b .

9 Discussion

Based on a list of desirable properties for risk sharing, this paper offers a systematic treatment of different risk-sharing rules for insurance losses, including the conditional mean risk-sharing rule and the newly proposed quantile risk-sharing rule. It works out an application to the dominant business model in P2P insurance, the pooled deductible system with comonotonic risk-sharing rules. Some methods for building new risk-sharing rules are also proposed. Applications to contingent risk funds and collective pools are discussed.

Some rules considered in this paper are nonparametric in the sense that they do not require the knowledge of the joint distribution of the losses comprised in the pool. This is the case for the order statistics, the multiple layer and the uniform risk-sharing rules. Other ones are very easy to implement since they only involve elementary quantities, such as the mean proportional risk-sharing rule that only uses expected losses or the scale-proportional risk-sharing rule. The quantile risk-sharing rule requires the knowledge of the marginal distribution of the losses comprised in the pool, but it does not use their dependence structure. In that respect, the quantile rule is copula-free. Finally, the conditional mean risk-sharing rule requires full knowledge of the joint distribution of the losses in the pool. Its implementation obviously necessitates more computational efforts but all properties discussed in Section 3, except comonotonicity are satisfied. Change of distributions may ease computations and the conditional mean risk-sharing rule reduces to simpler rules under some modified distribution.

The risk-sharing rules studied in this paper are very helpful to better understand commercial insurance. Consider individual losses X_i such that $s \mapsto E[X_i|S_n = s]$ are continuously increasing for all i . If not then individual i should not join the pool because he or she could benefit from an increase in S_n and thus has interests conflicting with other participants. Consider the case of a commercial insurance company having to pay a rate of return r_{roc} on the solvency capital put at its disposal. Assume that the solvency capital is obtained from the Value-at-Risk at probability level 99.5% as under Solvency 2 in the European Union. The total solvency capital $\text{VaR}[S_n; 99.5\%] - E[S_n]$ can be decomposed into

$$\begin{aligned} \text{VaR}[S_n; 99.5\%] - E[S_n] &= \text{VaR}\left[\sum_{i=1}^n E[X_i|S_n]; 99.5\%\right] - \sum_{i=1}^n E[X_i] \\ &= \sum_{i=1}^n \left(\text{VaR}[E[X_i|S_n]; 99.5\%] - E[X_i]\right) \\ &= \sum_{i=1}^n \left(E[X_i|S_n = \text{VaR}[S_n; 99.5\%]] - E[X_i]\right). \end{aligned}$$

Policyholders then receive the loss amount X_i ex post in exchange of the ex-ante premium

$$\pi[X_i; S_n] = E[X_i] + r_{\text{roc}} \left(E[X_i|S_n = \text{VaR}[S_n; 99.5\%]] - E[X_i] \right)$$

where we recognize the conditional mean risk-sharing rule applied to $s = \text{VaR}[S_n; 99.5\%]$. This appears to be an appropriate economic premium calculation principle. Similar formulas hold true replacing the conditional mean risk-sharing rule with any comonotonic risk-sharing rule.

A better understanding of risk-sharing rules for insurance losses also opens the door to a new generation of participating insurance contracts. As explained in Section 7, a lower layer can be shared among policyholders while the insurer covers the upper layer, guaranteeing that individual contributions never exceed a given threshold d_i for participant i . Formally, participant i contributes $\min\{H_i(S_n), d_i\}$ whereas the insurer issuing the participating insurance contract covers $\sum_{i=1}^n (H_i(S_n) - d_i)_+$. The properties proposed in the present paper help to select an appropriate rule depending on the specific circumstances where risk sharing operates.

Of course, one can imagine other properties than those proposed in this paper, such as the monotonicity property proposed by Chen et al. (2017) which requires introducing risk measures whereas comparisons are based on the convex order in this paper. The monotonicity property could be expressed in the present setting as follows: a new entry in the pool will not lead to higher risks allocated to existing participants in terms of convex order. Precisely, considering a pool $\mathbf{X}_n$ including participant i and a larger pool $\mathbf{X}_{n+k}$, $k \geq 1$, supplementing the pool $\mathbf{X}_n$ with additional losses $X_{n+1}, \dots, X_{n+k}$, then $H_i(\mathbf{X}_{n+k}) \preceq_{\text{CX}} H_i(\mathbf{X}_n)$. In some sense, this is a generalization of the willingness-to-join property. The conditional mean risk-sharing rule satisfies this property for independent losses and the uniform risk-sharing rule fulfills it for exchangeable losses, for instance.

Acknowledgements

The authors thank Alex Kukush for helpful comments about an earlier version of the paper. Jan Dhaene acknowledges the financial support of BOF KU Leuven (project C14/21/089).

References

- Abdikerimova, S., Feng, R. (2021). Peer-to-Peer multi-risk insurance and mutual aid. *European Journal of Operational Research*, in press.
- Albrecht, P., Huguenberger, M. (2017). The fundamental theorem of mutual insurance. *Insurance: Mathematics and Economics* 75, 180-188.
- Bourles, R., Bramouille, Y., Perez-Richet, E. (2021). Altruism and risk sharing in networks. *Journal of the European Economic Association* 19, 1488-1521.
- Carlier, G., Dana, R. A. (2003). Pareto efficient insurance contracts when the insurer's cost function is discontinuous. *Economic Theory* 21, 871-893.
- Charpentier, A., Kouakou, L., Lowe, M., Ratz, P., Vermet, F. (2021). Collaborative insurance sustainability and network structure. *arXiv preprint arXiv:2107.02764*.

- Chen, X., Hu, Z., Wang, S. (2017). Stable risk sharing and its monotonicity. Available at SSRN: <https://ssrn.com/abstract=2987631>
- Deelstra, G., Dhaene, J., Vanmaele, M. (2010). An overview of comonotonicity and its applications in finance and insurance. *Advanced Mathematical Methods for Finance* (editors: Øksendal, B. and Nunno, G.). Springer, Germany (Heidelberg).
- Denneberg, D. (1994). *Non-Additive Measure and Integral*. Kluwer Academic Publishers, Boston.
- Denuit, M. (2019). Size-biased transform and conditional mean risk sharing, with application to P2P insurance and tontines. *ASTIN Bulletin* 49, 591-617.
- Denuit, M. (2020). Investing in your own and peers' risks: The simple analytics of P2P insurance. *European Actuarial Journal* 10, 335-359.
- Denuit, M., Dhaene, J. (2012). Convex order and comonotonic conditional mean risk sharing. *Insurance: Mathematics and Economics* 51, 265-270.
- Denuit, M., Dhaene, J., Goovaerts, M.J., Kaas, R. (2005). *Actuarial Theory for Dependent Risks: Measures, Orders and Models*. Wiley, New York.
- Denuit, M., Robert, C.Y. (2020). Large-loss behavior of conditional mean risk sharing. *ASTIN Bulletin* 50, 1093-1122.
- Denuit, M., Robert, C.Y. (2021a). From risk sharing to pure premium for a large number of heterogeneous losses. *Insurance: Mathematics and Economics* 96, 116-126.
- Denuit, M., Robert, C.Y. (2021b). Collaborative insurance with stop-loss protection and team partitioning. *North American Actuarial Journal*, in press.
- Denuit, M., Robert, C.Y. (2021c). Risk sharing under the dominant peer-to-peer property and casualty insurance business models. *Risk Management and Insurance Review* 24, 181-205.
- Denuit, M., Robert, C.Y. (2021d). Polynomial series expansion and moment approximations for the conditional mean risk sharing of insurance losses. *Methodology and Computing in Applied Probability*, in press.
- Denuit, M., Robert, C.Y. (2021e). Efron's asymptotic monotonicity property in the Gaussian stable domain of attraction. *Journal of Multivariate Analysis* 186, Article 104803.
- Denuit, M., Robert, C.Y. (2021f). Corrigendum and addendum to "From risk sharing to pure premium for a large number of heterogeneous losses". *Insurance: Mathematics and Economics* 101, 640-644.
- Denuit, M., Robert, C.Y. (2021g). Conditional tail expectation decomposition and conditional mean risk sharing for dependent and conditionally independent risks. *Methodology and Computing in Applied Probability*, in press.

- Denuit, M., Robert, C.Y. (2021h). Conditional mean risk sharing in the individual model with graphical dependencies. *Annals of Actuarial Science*, in press.
- Dhaene, J., Denuit, M., Goovaerts, M.J., Kaas, R., Vyncke, D. (2002a). The concept of comonotonicity in actuarial science and finance: Theory. *Insurance: Mathematics and Economics* 31, 3-33.
- Dhaene, J., Denuit, M., Goovaerts, M.J., Kaas, R., Vyncke, D. (2002b). The concept of comonotonicity in actuarial science and finance: Applications. *Insurance: Mathematics and Economics* 31, 133-161.
- Dhaene, J., Linders, D. (2019). *Foundations of Risk Measurement*. Unpublished Lecture Notes.
- Embrechts, P., Liu, H., Wang, R. (2018). Quantile-based risk sharing. *Operations Research* 66, 936-949.
- Feng, R., Liu, C., Taylor, S. M. (2020). Peer-to-peer risk sharing with an application to flood risk pooling. Available at SSRN 3754565.
- Filipovic, D., Svindland, G. (2008). Optimal capital and risk allocations for law-and cash-invariant convex functions. *Finance and Stochastics* 12, 423-439.
- Goovaerts, M.J., De Vijlder, F.E., Haezendonck, J. (1984). *Insurance Premiums: Theory and Applications*. North-Holland. Amsterdam.
- Hieber, P., Lucas, N. (2020). Modern life-care tontines. Available at SSRN: <https://ssrn.com/abstract=3688386>
- Schumacher, J.M. (2018). Linear versus nonlinear allocation rules in risk sharing under financial fairness. *ASTIN Bulletin* 48, 995-1024.
- Shaked, M., Shanthikumar, J.G. (2007). *Stochastic Orders*. Springer, New York.
- Skogh, G., Wu, H. (2005). The diversification theorem restated: Risk-pooling without assignment of probabilities. *Journal of Risk and Uncertainty* 31, 35-51.
- von Bieberstein, F., Feess, E., Fernando, J. F., Kerzenmacher, F., Schiller, J. (2019). Moral hazard, risk sharing, and the optimal pool size. *Journal of Risk and Insurance* 86, 297-313.

APPENDIX

A Proof of Proposition 4.2

Reshuffling property The reshuffling property is valid since individual contributions $H_i^{\text{cm}}(S_n)$ only depend on (X_i, S_n) which is not modified by reshuffling.

Normalization property The normalization property is valid since $S_n = S_{n-1}$ when $\mathbf{X}_n = (X_1, X_2, \dots, X_{n-1}, 0)$ and $\mathbf{X}_{n-1} = (X_1, X_2, \dots, X_{n-1})$.

Translativity property Translativity holds true since, for all $i \neq n$,

$$H_i^{\text{cm}}(\mathbf{X}_n + c \mathbf{1}_{n,n}) = \mathbb{E}[X_i | S_n + c] = \mathbb{E}[X_i | S_n] = H_i^{\text{cm}}(\mathbf{X}_n).$$

Positive homogeneity property Also, positive homogeneity holds true since

$$H_i^{\text{cm}}(c\mathbf{X}_n) = \mathbb{E}[cX_i | cS_n] = c\mathbb{E}[X_i | S_n] = cH_i^{\text{cm}}(S_n).$$

Constancy property Turning to the constancy property, let $\mathbf{X}_n = (X_1, X_2, \dots, X_{n-1}, c)$, for some constant c , and let $\mathbf{X}_{n-1} = (X_1, X_2, \dots, X_{n-1})$. Then we have that, for any $i \neq n$,

$$H_i^{\text{cm}}(\mathbf{X}_n) = \mathbb{E}[X_i | S_n] = \mathbb{E}[X_i | S_{n-1} + c] = \mathbb{E}[X_i | S_{n-1}] = H_i^{\text{cm}}(\mathbf{X}_{n-1}).$$

No-ripoff property The no-ripoff property is valid since

$$H_i^{\text{cm}}(\mathbf{X}_n) = \mathbb{E}[X_i | S_n] \leq \mathbb{E}[F_i^{-1}(1) | S_n] = F_i^{-1}(1), \text{ for any } i = 1, 2, \dots, n.$$

Actuarial fairness property Actuarial fairness holds true because

$$\mathbb{E}[H_i^{\text{cm}}(\mathbf{X}_n)] = \mathbb{E}[\mathbb{E}[X_i | S_n]] = \mathbb{E}[X_i], \text{ for any } i = 1, 2, \dots, n.$$

Willingness-to-join property The willingness-to-join property is valid since

$$\mathbb{E}[X_i | S_n] \preceq_{\text{CX}} X_i \text{ holds for every } i = 1, 2, \dots, n,$$

Fair-merging property The fair-merging property holds true since, for any $k \neq l$,

$$H_i^{\text{cm}}(\mathbf{X}_n + X_l \times (\mathbf{1}_{k,n} - \mathbf{1}_{l,n})) = \mathbb{E}[X_i | S_n] = H_i^{\text{cm}}(\mathbf{X}_n) \text{ if } i \text{ is different from } k \text{ and } l,$$

Fair-splitting property The fair-splitting property holds true since, for any $k \in 1, 2, \dots, n$, and any non-negative random variables X'_k and X_{n+1} satisfying $X_k = X'_k + X_{n+1}$, one has that, for any i different from k and $n+1$

$$H_i^{\text{cm}}((\mathbf{X}_n + (X'_k - X_k) \times \mathbf{1}_{k,n}, X_{n+1})) = \mathbb{E}[X_i | S_n] = H_i^{\text{cm}}(\mathbf{X}_n).$$

Stand-alone property for comonotonic losses Finally, the stand-alone property for comonotonic losses follows from Proposition 5.9. Indeed, if $\mathbf{X}_n$ is comonotonic then $X_i = h_i(S_n)$ for the non-decreasing functions h_i defined in (5.15). Therefore,

$$H_i^{\text{cm}}(S_n) = \mathbb{E}[h_i(S_n) | S_n] = h_i(S_n) = X_i.$$

Comonotonicity property The conditional mean risk-sharing rule satisfies the comonotonicity property only if, $s \mapsto \mathbb{E}[X_i | S_n = s]$ is non-decreasing for any $i \in 1, 2, \dots, n$. This is not true in general. We refer the reader to Denuit and Robert (2021a) for a counter-example involving independent zero-augmented Gamma-distributed risks.

B Proof of Proposition 5.7

Reshuffling property The quantile risk-sharing rule satisfies the reshuffling property since the distributions of S_n and S_n^c are not modified by reshuffling.

Normalization property The quantile risk-sharing rule satisfies the normalization property since $S_n = S_{n-1}$ and $S_n^c = S_{n-1}^c$ when $\mathbf{X}_n = (X_1, X_2, \dots, X_{n-1}, 0)$ and $\mathbf{X}_{n-1} = (X_1, X_2, \dots, X_{n-1})$.

Translativity property The quantile risk-sharing rule satisfies the translativity property since, for all $i \neq n$,

$$H_i^{\text{quant}}(\mathbf{X}_n + c \mathbf{1}_{n,n}) = F_i^{-1(\alpha_{S_n+c})}(F_{S_n^c+c}(S_n + c)) = F_i^{-1(\alpha_{S_n+c})}(F_{S_n^c}(S_n))$$

with

$$\begin{aligned} \alpha_{S_n+c} &= \frac{F_{S_n+c}^{-1+}(F_{S_n+c}(S_n + c)) - S_n - c}{F_{S_n+c}^{-1+}(F_{S_n+c}(S_n + c)) - F_{S_n+c}^{-1}(F_{S_n+c}(S_n + c))} \\ &= \frac{F_{S_n}^{-1+}(F_{S_n}(S_n)) - S_n}{F_{S_n}^{-1+}(F_{S_n}(S_n)) - F_{S_n}^{-1}(F_{S_n}(S_n))} = \alpha_{S_n}. \end{aligned}$$

Positive homogeneity property The proof of the positive homogeneity property follows the same lines as the one of the translativity property.

Constancy property Considering the constancy property, let $\mathbf{X}_n = (X_1, X_2, \dots, X_{n-1}, c)$, for some constant c , and let $\mathbf{X}_{n-1} = (X_1, X_2, \dots, X_{n-1})$. Then we have that, for any $i \neq n$,

$$H_i^{\text{quant}}(\mathbf{X}_n) = F_i^{-1(\alpha_{S_{n-1}+c})}(F_{S_{n-1}^c+c}(S_{n-1} + c)) = F_i^{-1(\alpha_{S_{n-1}+c})}(F_{S_{n-1}^c}(S_{n-1}))$$

with

$$\begin{aligned} \alpha_{S_{n-1}+c} &= \frac{F_{S_{n-1}+c}^{-1+}(F_{S_{n-1}+c}(S_{n-1} + c)) - S_{n-1} - c}{F_{S_{n-1}+c}^{-1+}(F_{S_{n-1}+c}(S_{n-1} + c)) - F_{S_{n-1}+c}^{-1}(F_{S_{n-1}+c}(S_{n-1} + c))} \\ &= \frac{F_{S_{n-1}}^{-1+}(F_{S_{n-1}}(S_{n-1})) - S_{n-1}}{F_{S_{n-1}}^{-1+}(F_{S_{n-1}}(S_{n-1})) - F_{S_{n-1}}^{-1}(F_{S_{n-1}}(S_{n-1}))} = \alpha_{S_{n-1}}. \end{aligned}$$

Hence the quantile risk-sharing rule satisfies the constancy property.

No-ripoff property The no-ripoff property is valid since

$$H_i^{\text{quant}}(\mathbf{X}_n) = F_i^{-1}(\alpha_{S_n}) (F_{S_n^c}(S_n)) \leq F_i^{-1}(1) \text{ for any } i = 1, 2, \dots, n.$$

Comonotonicity property The quantile risk-sharing rule satisfies the comonotonicity property by construction as $F_i^{-1}(\alpha_s)(F_{S_n^c}(s))$ is non-decreasing in s .

Stand-alone property for comonotonic losses Every comonotonic pool is left unchanged by the quantile risk-sharing pool so that the stand-alone property for comonotonic losses is valid. See Proposition 5.11.

Actuarial fairness property To show that the quantile risk-sharing rule does not necessarily satisfy the actuarial fairness property, let us consider the case where $n = 2$, X_1 has distribution function F and X_2 has distribution function $F \circ g^{-1}$ where g is a positive, continuous and increasing function. We have

$$\begin{aligned} \mathbb{P} [H_1^{\text{quant}}(\mathbf{X}_2) > v] &= \mathbb{P} [S_2 > (F^{-1} + g \circ F^{-1}) \circ F(v)] \\ &= \mathbb{P} [S_2 > v + g(v)] \\ &= \mathbb{P} [h^{-1}(S_2) > v] \end{aligned}$$

with $h(v) = v + g(v)$. It follows that

$$\mathbb{E} [H_1^{\text{quant}}(\mathbf{X}_2)] = \mathbb{E} [h^{-1}(X_1 + g(Z_1))] = \mathbb{E} [h^{-1}(X_1 - Z_1 + h(Z_1))]$$

where Z_1 has the same distribution as X_1 . If X_1 and Z_1 are comonotonic or g is a linear function, then $\mathbb{E} [H_1^{\text{quant}}(\mathbf{X}_2)] = \mathbb{E} [X_1]$. But this is not true in general.

Willingness-to-join property The quantile risk-sharing rule cannot always be beneficial for all risk-averse individuals since it does not always satisfy the fairness property. Hence the willingness-to-join property is not necessarily valid.

Fair-merging property Moving to the fair-merging property, the quantile risk-sharing rule does not necessarily satisfy it since, for any $k \neq l$, $F_{X_k+X_l}^{-1}(p)$ is not always equal to $F_{X_k}^{-1}(p) + F_{X_l}^{-1}(p)$ if X_k and X_l are not comonotonic.

Fair-splitting property Following the same reasoning as for the fair-merging property, the quantile risk-sharing rule does not necessarily satisfy the fair-splitting property.

C Proof of Proposition 5.9

First, suppose that $\mathbf{X}_n$ is comonotonic. We define the connected support of $\mathbf{X}_n$ as follows:

$$\left\{ \left(F_1^{-1(\alpha)}(p), F_2^{-1(\alpha)}(p), \dots, F_n^{-1(\alpha)}(p) \right) \mid p \in [0, 1] \text{ and } \alpha \in [0, 1] \right\}, \quad (\text{C.1})$$

similar to the one introduced in formula (29) of Dhaene et al. (2002a). By convention, we set $F_i^{-1(\alpha)}(0) = F_i^{-1+}(0)$ and $F_i^{-1(\alpha)}(1) = F_i^{-1}(1)$. Let $\mathbf{x}_n = (x_1, x_2, \dots, x_n)$ be an element of this connected support and let $s = \sum_{i=1}^n x_i$. Following a reasoning similar to the one of the proof of Theorem 7 in Dhaene et al. (2002a), we find that $\mathbf{x}_n$ is the unique point of the intersection of the connected support and the hyperplane $\{(y_1, y_2, \dots, y_n) \mid \sum_{i=1}^n y_i = s\}$. As the point $(h_1(s), h_2(s), \dots, h_n(s))$ with the h_i defined in (5.15) is an element of the connected support of $\mathbf{X}_n$, and moreover, $\sum_{i=1}^n h_i(s) = s$ so that $(h_1(s), h_2(s), \dots, h_n(s))$ is a point of the hyperplane considered above, we find that

$$\mathbf{x}_n = (h_1(s), h_2(s), \dots, h_n(s)). \quad (\text{C.2})$$

As this expression hold for any point $\mathbf{x}_n$ of the connected support of $\mathbf{X}_n$, we can conclude that (5.14) holds.

Conversely, let us assume that $\mathbf{X}_n$ is given by (5.14), with the functions h_i defined in (5.15). As the functions h_i are all non-decreasing, it follows immediately that $\mathbf{X}_n$ is comonotonic, see e.g. Theorem 3 in Dhaene et al. (2002a).

Remark C.1. The characterization of comonotonicity in Proposition 5.9 is similar to the one established in the bivariate case by Denneberg (1994, Prop. 4.5, item v). While Denneberg (1994) only proves the existence of functions h_i , explicit expressions of h_i are given here.

D Proof that the network-based conditional mean risk-sharing rule satisfies the full loss allocation condition

It suffices to write

$$\begin{aligned}
\sum_{i=1}^n H_i(\mathbf{X}_n) &= \sum_{i=1}^n H_{ii}(S_{\mathbf{w},i}) + \sum_{i=1}^n \sum_{j \in \mathcal{C}(i)} H_{ji}(S_{\mathbf{w},j}) \\
&= \sum_{i=1}^n \mathbb{E}[w_{ii}X_i | S_{\mathbf{w},i}] + \sum_{i=1}^n \sum_{j \in \mathcal{C}(i)} \mathbb{E}[w_{ji}X_j | S_{\mathbf{w},j}] \\
&= \sum_{i=1}^n \mathbb{E}[w_{ii}X_i | S_{\mathbf{w},i}] + \sum_{i=1}^n \sum_{j \in \mathcal{C}(i)} \mathbb{E}[w_{ji}X_j | S_{\mathbf{w},i}] \\
&= \sum_{i=1}^n \mathbb{E} \left[w_{ii}X_i + \sum_{j \in \mathcal{C}(i)} w_{ji}X_j \middle| S_{\mathbf{w},i} \right] \\
&= \sum_{i=1}^n S_i = \sum_{i=1}^n \left(w_{ii}X_i + \sum_{j \in \mathcal{C}(i)} w_{ji}X_j \right) \\
&= \sum_{i=1}^n w_{ii}X_i + \sum_{i=1}^n \sum_{j \in \mathcal{C}(i)} w_{ji}X_j = \sum_{i=1}^n w_{ii}X_i + \sum_{i=1}^n \sum_{j \in \mathcal{C}(i)} w_{ij}X_i \\
&= \sum_{i=1}^n X_i \left(w_{ii} + \sum_{j \in \mathcal{C}(i)} w_{ij} \right) = \sum_{j=1}^n X_j.
\end{aligned}$$

The full loss allocation condition (2.2) is therefore fulfilled.

E Proof that H^{coll} is actuarially fair

Notice that ex ante, $\beta_{ik} = \beta_{ik}(X_k)$. To show that $\mathbb{E}[H_i^{\text{coll}}(\mathbf{X}_m)] = \mathbb{E}[X_i]$ indeed holds true, it suffices to write

$$\mathbb{E}[H_i^{\text{coll}}(\mathbf{X}_m)] = \sum_{k=1}^m \mathbb{E}[\beta_{ik}(X_k)X_k]$$

with

$$\mathbb{E}[\beta_{ik}(X_k)X_k] = \int_0^\infty \frac{f_i(x)}{\sum_{j=1}^n f_j(x)} x f_k(x) dx.$$

Thus, we have

$$\begin{aligned}
\mathbb{E}[H_i^{\text{coll}}(\mathbf{X}_m)] &= \int_0^\infty \frac{f_i(x)}{\sum_{j=1}^n f_j(x)} x \left(\sum_{k=1}^n f_k(x) \right) dx \\
&= \int_0^\infty x f_i(x) dx \\
&= \mathbb{E}[X_i]
\end{aligned}$$

which ends the proof.