

## 1 Variance estimation for multi-stage sampling

Let  $U$  be a finite population and  $\mathcal{P}(U)$  the power set of  $U$ . Let  $p : \mathcal{S} \rightarrow (0, 1]$  be a  $r$ -stage sampling design ( $r \geq 2$ ), where  $\mathcal{S} \subset \mathcal{P}(U)$  is the set of all admissible samples under the design  $p$ . We express the hierarchical structure of the population  $U$ , with respect to the  $r$ -stage design  $p$ , as follows:

$$U = \bigsqcup_{i \in U^{(1)}} U_i^{(2+)} = \bigsqcup_{i \in U^{(1)}} \bigsqcup_{a \in U_i^{(2)}} U_{ia}^{(3)} = \cdots = \bigsqcup_{i \in U^{(1)}} \cdots \bigsqcup_{b \in U_{i \dots}^{(r-1)}} U_{i \dots b}^{(r)} \quad (1.1)$$

where  $U^{(1)}$  is the set of all primary sampling units (PSU), and for each PSU  $i \in U^{(1)}$ ,  $U_i^{(2)}$  denotes the set of all secondary sampling units (SSU) contained in  $i \in U^{(1)}$ , and for each SSU  $a \in U_i^{(2)}$ ,  $U_{ia}^{(3)}$  denotes the set of all tertiary sampling units (TSU) contained in  $a \in U_i^{(2)}$ , and so on. Similarly, we express the hierarchical structure of every admissible sample  $s \in \mathcal{S}$  as follows:

$$s = \bigsqcup_{i \in s^{(1)}} s_i^{(2+)} = \bigsqcup_{i \in s^{(1)}} \bigsqcup_{a \in s_i^{(2)}} s_{ia}^{(3)} = \cdots \quad (1.2)$$

Let  $y : U \rightarrow \mathbb{R}$  be a population characteristic. Let  $T$  be its population total, i.e.

$$T = \sum_{u \in U} y_u = \sum_{i \in U^{(1)}} T_i = \sum_{i \in U^{(1)}} \sum_{a \in U_{ia}^{(2)}} T_{ia} = \cdots = \sum_{i \in U^{(1)}} \cdots \sum_{u \in U_{i \dots}^{(r)}} y_u \quad (1.3)$$

### Theorem 1.1

If  $\hat{T}_i : \mathcal{S}_i^{(2+)} \rightarrow \mathbb{R}$  is an unbiased estimator for  $T_i$ , for each PSU  $i \in U^{(1)}$ , then the random variable  $\hat{T} : \mathcal{S} \rightarrow \mathbb{R}$  defined as follows:

$$\hat{T}(s) := \sum_{i \in s^{(1)}} \frac{\hat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \quad (1.4)$$

is a design-unbiased estimator for

$$T = \sum_{i \in U^{(1)}} T_i$$

If the  $r$ -stage sampling design has invariant and independent subsampling, then the design-variance of  $\hat{T}$  is given by:

$$\text{Var}[\hat{T}] = \underbrace{\text{Var}^{(1)}\left(E^{(2+)}(\hat{T} \mid s^{(1)})\right)}_{V_{\text{PSU}}} + \underbrace{E^{(1)}\left(\text{Var}^{(2+)}(\hat{T} \mid s^{(1)})\right)}_{V_{\text{subsampling}}}, \quad (1.5)$$

where

$$\begin{aligned} \text{Var}^{(1)}\left(E^{(2+)}(\hat{T} \mid s^{(1)})\right) &= \sum_{i \in U^{(1)}} \sum_{j \in U^{(1)}} \Delta_{ij}^{(1)} \frac{T_i}{\pi_i^{(1)}} \frac{T_j}{\pi_j^{(1)}}, \quad \text{and} \\ E^{(1)}\left(\text{Var}^{(2+)}(\hat{T} \mid s^{(1)})\right) &= \sum_{i \in U^{(1)}} \frac{V_i}{\pi_i^{(1)}}, \end{aligned}$$

with

$$V_i := \text{Var}^{(2+)}[\hat{T}_i] \quad \text{and} \quad \Delta_{ij}^{(1)} := \begin{cases} \pi_i^{(1)} (1 - \pi_i^{(1)}), & \text{if } i = j \\ \pi_{ij}^{(1)} - \pi_i^{(1)} \pi_j^{(1)}, & \text{if } i \neq j \end{cases} \quad (1.6)$$

# Multi-stage Sampling

Furthermore, if  $\widehat{V}_i : \mathcal{S}_i^{(2+)} \rightarrow \mathbb{R}$  is an unbiased estimator for  $V_i := \text{Var}^{(2+)}[\widehat{T}_i]$ , and  $\pi_i^{(1)} > 0$ ,  $\pi_{ij}^{(1)} > 0$  for any PSU  $i, j \in U^{(1)}$ , then

$$\begin{aligned}\widehat{\text{Var}}[\widehat{T}](s) &:= \sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} + \sum_{i \in s^{(1)}} \frac{\widehat{V}_i(s_i^{(2+)})}{\pi_i^{(1)}}, \\ \widehat{\text{Var}}^{(1)}[\widehat{T}](s) &:= \sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} + \sum_{i \in s^{(1)}} \left(1 - \frac{1}{\pi_i^{(1)}}\right) \frac{\widehat{V}_i(s_i^{(2+)})}{\pi_i^{(1)}}, \text{ and} \\ \widehat{\text{Var}}^{(2+)}[\widehat{T}](s) &:= \sum_{i \in s^{(1)}} \frac{\widehat{V}_i(s_i^{(2+)})}{\left(\pi_i^{(1)}\right)^2}\end{aligned}$$

are unbiased estimators for  $\text{Var}[\widehat{T}]$ ,  $V_{\text{PSU}} := \text{Var}^{(1)}\left(E^{(2+)}(\widehat{T} \mid s^{(1)})\right)$ , and  $V_{\text{subsampling}} := E^{(1)}\left(\text{Var}^{(2+)}(\widehat{T} \mid s^{(1)})\right)$ , respectively.

## Corollary 1.2

$$\widehat{\text{Var}}^{(1)}[\widehat{T}](s) = \widehat{\text{Var}}[\widehat{T}](s) - \widehat{\text{Var}}^{(2+)}[\widehat{T}](s) \quad (1.7)$$

PROOF

$$\begin{aligned}\text{Var}^{(1)}\left[E^{(2+)}\left[\widehat{T} \mid s^{(1)}\right]\right] &= \text{Var}^{(1)}\left[E^{(2+)}\left[\sum_{i \in s^{(1)}} \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \mid s^{(1)}\right]\right] \\ &= \text{Var}^{(1)}\left[\sum_{i \in s^{(1)}} \frac{E^{(2+)}[\widehat{T}_i(s_i^{(2+)})]}{\pi_i^{(1)}}\right] \\ &= \text{Var}^{(1)}\left[\sum_{i \in s^{(1)}} \frac{T_i}{\pi_i^{(1)}}\right] \\ &= \sum_{i \in U^{(1)}} \sum_{j \in U^{(1)}} \Delta_{ij}^{(1)} \frac{T_i}{\pi_i^{(1)}} \frac{T_j}{\pi_j^{(1)}} \\ E^{(1)}\left[\text{Var}^{(2+)}\left[\widehat{T} \mid s^{(1)}\right]\right] &= E^{(1)}\left[\text{Var}^{(2+)}\left[\sum_{i \in s^{(1)}} \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \mid s^{(1)}\right]\right] \\ &= E^{(1)}\left[\sum_{i \in s^{(1)}} \text{Var}^{(2+)}\left[\frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}}\right]\right] \\ &= E^{(1)}\left[\sum_{i \in s^{(1)}} \frac{\text{Var}^{(2+)}[\widehat{T}_i(s_i^{(2+)})]}{\left(\pi_i^{(1)}\right)^2}\right] \\ &= E^{(1)}\left[\sum_{i \in s^{(1)}} \frac{V_i/\pi_i^{(1)}}{\pi_i^{(1)}}\right] \\ &= \sum_{i \in U^{(1)}} \frac{V_i}{\pi_i^{(1)}}\end{aligned}$$

$$\begin{aligned}
 E\left(\widehat{\text{Var}}^{(2+)}(\widehat{T})\right) &= E\left(\sum_{i \in s^{(1)}} \frac{\widehat{V}_i(s_i^{(2+)})}{\left(\pi_i^{(1)}\right)^2}\right) = E^{(1)}\left(E^{(2+)}\left(\sum_{i \in s^{(1)}} \frac{\widehat{V}_i(s_i^{(2+)})/\pi_i^{(1)}}{\pi_i^{(1)}} \middle| s^{(1)}\right)\right) \\
 &= E^{(1)}\left(\sum_{i \in s^{(1)}} \frac{E^{(2+)}\left[\widehat{V}_i(s_i^{(2+)}) \middle| s^{(1)}\right]/\pi_i^{(1)}}{\pi_i^{(1)}}\right) = E^{(1)}\left(\sum_{i \in s^{(1)}} \frac{V_i/\pi_i^{(1)}}{\pi_i^{(1)}}\right) = \sum_{i \in U^{(1)}} \frac{V_i}{\pi_i^{(1)}} \\
 &= E^{(1)}\left(\text{Var}^{(2+)}(\widehat{T} \middle| s^{(1)})\right) = V_{\text{PSU}}
 \end{aligned}$$

Similarly,

$$\begin{aligned}
 E\left(\sum_{i \in s^{(1)}} \frac{\widehat{V}_i(s_i^{(2+)})}{\pi_i^{(1)}}\right) &= E^{(1)}\left(E^{(2+)}\left(\sum_{i \in s^{(1)}} \frac{\widehat{V}_i(s_i^{(2+)})}{\pi_i^{(1)}} \middle| s^{(1)}\right)\right) = E^{(1)}\left(\sum_{i \in s^{(1)}} \frac{E^{(2+)}\left[\widehat{V}_i(s_i^{(2+)}) \middle| s^{(1)}\right]}{\pi_i^{(1)}}\right) \\
 &= E^{(1)}\left(\sum_{i \in s^{(1)}} \frac{V_i}{\pi_i^{(1)}}\right) = \sum_{i \in U^{(1)}} V_i
 \end{aligned}$$

Next, observe that

$$\begin{aligned}
 E\left[\sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}}\right] &= E^{(1)}\left(E^{(2+)}\left(\sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} \middle| s^{(1)}\right)\right) \\
 &= E^{(1)}\left(\sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{E^{(2+)}\left[\widehat{T}_i(s_i^{(2+)}) \cdot \widehat{T}_j(s_j^{(2+)}) \middle| s^{(1)}\right]}{\pi_i^{(1)} \pi_j^{(1)}}\right)
 \end{aligned}$$

Now, observe (the key technical observation) that

$$E^{(2+)}\left[\widehat{T}_i(s_i^{(2+)}) \cdot \widehat{T}_j(s_j^{(2+)}) \middle| s^{(1)}\right] = E^{(2+)}\left[\widehat{T}_i(s_i^{(2+)}) \cdot \widehat{T}_j(s_j^{(2+)})\right] = \begin{cases} \text{Var}^{(2+)}(\widehat{T}_i) + E^{(2+)}(\widehat{T}_i)^2, & \text{if } i = j, \\ E^{(2+)}(\widehat{T}_i) \cdot E^{(2+)}(\widehat{T}_j), & \text{if } i \neq j \end{cases}$$

Hence,

$$\begin{aligned}
 E\left[\sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}}\right] &= E^{(1)}\left(\sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{E^{(2+)}\left[\widehat{T}_i(s_i^{(2+)}) \cdot \widehat{T}_j(s_j^{(2+)}) \middle| s^{(1)}\right]}{\pi_i^{(1)} \pi_j^{(1)}}\right) \\
 &= E^{(1)}\left(\sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{T_i}{\pi_i^{(1)}} \cdot \frac{T_j}{\pi_j^{(1)}} + \sum_{i \in s^{(1)}} \frac{(1 - \pi_i^{(1)}) V_i / \pi_i^{(1)}}{\pi_i^{(1)}}\right) \\
 &= \sum_{i \in U^{(1)}} \sum_{j \in U^{(1)}} \Delta_{ij}^{(1)} \cdot \frac{T_i}{\pi_i^{(1)}} \cdot \frac{T_j}{\pi_j^{(1)}} + \sum_{i \in U^{(1)}} \frac{(1 - \pi_i^{(1)})}{\pi_i^{(1)}} \cdot V_i \\
 &= \sum_{i \in U^{(1)}} \sum_{j \in U^{(1)}} \Delta_{ij}^{(1)} \cdot \frac{T_i}{\pi_i^{(1)}} \cdot \frac{T_j}{\pi_j^{(1)}} + \sum_{i \in U^{(1)}} \frac{V_i}{\pi_i^{(1)}} - \sum_{i \in U^{(1)}} V_i
 \end{aligned}$$

We may now establish that

$$\begin{aligned}
 E\left[\widehat{\text{Var}}(\hat{T})\right] &= E\left[\sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\hat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\hat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} + \sum_{i \in s^{(1)}} \frac{\hat{V}_i(s_i^{(2+)})}{\pi_i^{(1)}}\right] \\
 &= \left\{ \sum_{i \in U^{(1)}} \sum_{j \in U^{(1)}} \Delta_{ij}^{(1)} \cdot \frac{T_i}{\pi_i^{(1)}} \cdot \frac{T_j}{\pi_j^{(1)}} + \sum_{i \in U^{(1)}} \frac{V_i}{\pi_i^{(1)}} - \sum_{i \in U^{(1)}} V_i \right\} + \left\{ \sum_{i \in U^{(1)}} V_i \right\} \\
 &= \sum_{i \in U^{(1)}} \sum_{j \in U^{(1)}} \Delta_{ij}^{(1)} \cdot \frac{T_i}{\pi_i^{(1)}} \cdot \frac{T_j}{\pi_j^{(1)}} + \sum_{i \in U^{(1)}} \frac{V_i}{\pi_i^{(1)}} \\
 &= \text{Var}(\hat{T})
 \end{aligned}$$

Lastly, note that

$$\widehat{\text{Var}}^{(1)}[\hat{T}](s) = \widehat{\text{Var}}[\hat{T}](s) - \widehat{\text{Var}}^{(2+)}[\hat{T}](s)$$

Hence,

$$\begin{aligned}
 E\left[\widehat{\text{Var}}^{(1)}(\hat{T})\right] &= E\left[\widehat{\text{Var}}(\hat{T})\right] - E\left[\widehat{\text{Var}}^{(2+)}(\hat{T})\right] \\
 &= \text{Var}[\hat{T}] - E^{(1)}\left(\text{Var}^{(2+)}(\hat{T} \mid s^{(1)})\right) \\
 &= \text{Var}^{(1)}\left(E^{(2+)}(\hat{T} \mid s^{(1)})\right) + E^{(1)}\left(\text{Var}^{(2+)}(\hat{T} \mid s^{(1)})\right) - E^{(1)}\left(\text{Var}^{(2+)}(\hat{T} \mid s^{(1)})\right) \\
 &= \text{Var}^{(1)}\left(E^{(2+)}(\hat{T} \mid s^{(1)})\right) = V_{\text{subsampling}}
 \end{aligned}$$

□

## 2 Variance estimation for three-stage sampling

Let  $U$  be a finite population and  $\mathcal{P}(U)$  the power set of  $U$ . Let  $p : \mathcal{S} \rightarrow (0, 1]$  be a three-stage sampling design, where  $\mathcal{S} \subset \mathcal{P}(U)$  is the set of all admissible samples under the design  $p$ . We express the three-stage structure of the population  $U$ , with respect to the three-stage design  $p$ , as follows:

$$U = \bigsqcup_{i \in U^{(1)}} U_i^{(2+)} = \bigsqcup_{i \in U^{(1)}} \bigsqcup_{a \in U_i^{(2)}} U_{ia}^{(3)}, \quad (2.1)$$

where  $U^{(1)}$  is the set of all primary sampling units (PSU), and for each PSU  $i \in U^{(1)}$ ,  $U_i^{(2)}$  denotes the set of all secondary sampling units (SSU) contained in  $i \in U^{(1)}$ , and for each SSU  $a \in U_i^{(2)}$ ,  $U_{ia}^{(3)}$  denotes the set of all tertiary sampling units (TSU) contained in  $a \in U_i^{(2)}$ . Similarly, we express the three-stage structure of every admissible sample  $s \in \mathcal{S}$  as follows:

$$s = \bigsqcup_{i \in s^{(1)}} s_i^{(2+)} = \bigsqcup_{i \in s^{(1)}} \bigsqcup_{a \in s_i^{(2)}} s_{ia}^{(3)} \quad (2.2)$$

Let  $y : U \rightarrow \mathbb{R}$  be a population characteristic. Let  $T$  be its population total, i.e.

$$T = \sum_{u \in U} y_u = \sum_{i \in U^{(1)}} T_i = \sum_{i \in U^{(1)}} \sum_{a \in U_i^{(2)}} T_{ia} = \sum_{i \in U^{(1)}} \sum_{a \in U_i^{(2)}} \sum_{u \in U_{ia}^{(3)}} y_u \quad (2.3)$$

### Theorem 2.1

For a three-stage sampling design with invariant and independent subsampling,

1. The random variable  $\hat{T} : \mathcal{S} \rightarrow \mathbb{R}$ , defined as follows:

$$\hat{T}(s) := \sum_{i \in s^{(1)}} \frac{\hat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} = \sum_{i \in s^{(1)}} \frac{1}{\pi_i^{(1)}} \left( \sum_{a \in s_i^{(2)}} \frac{\hat{T}_{ia}(s_{ia}^{(3)})}{\pi_{i|a}^{(2)}} \right) = \sum_{i \in s^{(1)}} \frac{1}{\pi_i^{(1)}} \left( \sum_{a \in s_i^{(2)}} \frac{1}{\pi_{i|a}^{(2)}} \left( \sum_{u \in s_{ia}^{(3)}} \frac{y_u}{\pi_{ia|u}^{(3)}} \right) \right)$$

is a design-unbiased estimator for  $T$ , i.e.  $E[\hat{T}] = T$ .

2. If the three-stage sampling design has invariant and independent subsampling, then the design-variance of  $\hat{T}$  can be given by:

$$\begin{aligned} & \text{Var}[\hat{T}] \\ &= \text{Var}^{(1)}\left(E^{(2+)}\left(\hat{T} \mid s^{(1)}\right)\right) + E^{(1)}\left(\text{Var}^{(2+)}\left(\hat{T} \mid s^{(1)}\right)\right) \\ &= \text{Var}^{(1)}\left(E^{(2+)}\left(\hat{T} \mid s^{(1)}\right)\right) + E^{(1)}\left\{\text{Var}^{(2)}\left(E^{(3)}\left(\hat{T} \mid s^{(2)}\right) \mid s^{(1)}\right) + E^{(2)}\left(\text{Var}^{(3)}\left(\hat{T} \mid s^{(2)}\right) \mid s^{(1)}\right)\right\} \\ &= \underbrace{\text{Var}^{(1)}\left(E^{(2+)}\left(\hat{T} \mid s^{(1)}\right)\right)}_{V_{\text{PSU}}} + \underbrace{E^{(1)}\left\{\text{Var}^{(2)}\left(E^{(3)}\left(\hat{T} \mid s^{(2)}\right) \mid s^{(1)}\right)\right\}}_{V_{\text{SSU}}} + \underbrace{E^{(1)}\left\{E^{(2)}\left(\text{Var}^{(3)}\left(\hat{T} \mid s^{(2)}\right) \mid s^{(1)}\right)\right\}}_{V_{\text{TSU}}} \end{aligned}$$

where

$$\begin{aligned} V_{\text{PSU}} &:= \text{Var}^{(1)}\left(E^{(2+)}\left(\hat{T} \mid s^{(1)}\right)\right) = \sum_{i \in U^{(1)}} \sum_{j \in U^{(1)}} \Delta_{ij}^{(1)} \frac{T_i}{\pi_i^{(1)}} \frac{T_j}{\pi_j^{(1)}}, \\ V_{\text{SSU}} &:= E^{(1)}\left\{\text{Var}^{(2)}\left(E^{(3)}\left(\hat{T} \mid s^{(2)}\right) \mid s^{(1)}\right)\right\} = \sum_{i \in U^{(1)}} \frac{V_i^{(2)}}{\pi_i^{(1)}}, \quad \text{and} \\ V_{\text{TSU}} &:= E^{(1)}\left\{E^{(2)}\left(\text{Var}^{(3)}\left(\hat{T} \mid s^{(2)}\right) \mid s^{(1)}\right)\right\} = \sum_{i \in U^{(1)}} \frac{1}{\pi_i^{(1)}} \left( \sum_{a \in U_i^{(2)}} \frac{V_{ia}^{(3)}}{\pi_{i|a}^{(2)}} \right), \end{aligned}$$

with

$$\begin{aligned} \Delta_{ij}^{(1)} &:= \begin{cases} \pi_i^{(1)} (1 - \pi_i^{(1)}), & \text{if } i = j \\ \pi_{ij}^{(1)} - \pi_i^{(1)} \pi_j^{(1)}, & \text{if } i \neq j \end{cases} \\ V_i^{(2)} &:= \text{Var}^{(2)}\left[\sum_{a \in s_i^{(2)}} \frac{T_{ia}}{\pi_{i|a}^{(2)}}\right] = \sum_{a \in U_i^{(2)}} \sum_{b \in U_i^{(2)}} \Delta_{i|ab}^{(2)} \cdot \frac{T_{ia}}{\pi_{i|a}^{(2)}} \cdot \frac{T_{ib}}{\pi_{i|b}^{(2)}} \\ \Delta_{i|ab}^{(2)} &:= \begin{cases} \pi_{i|a}^{(2)} (1 - \pi_{i|a}^{(2)}), & \text{if } a = b \\ \pi_{i|ab}^{(2)} - \pi_{i|a}^{(2)} \pi_{i|b}^{(2)}, & \text{if } a \neq b \end{cases} \\ V_{ia}^{(3)} &:= \text{Var}^{(3)}\left(\hat{T}_{ia} \mid s^{(1)}, s^{(2)}\right) \end{aligned}$$

## Theorem 2.2

For a three-stage sampling design  $p : \mathcal{S} \subset \mathcal{P}(U) \rightarrow \mathbb{R}$  with invariant and independent subsampling, let  $\hat{T} : \mathcal{S} \rightarrow \mathbb{R}$  be the random variable defined as follows:

$$\hat{T}(s) := \sum_{i \in s^{(1)}} \frac{\hat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} = \sum_{i \in s^{(1)}} \frac{1}{\pi_i^{(1)}} \left( \sum_{a \in s_i^{(2)}} \frac{\hat{T}_{ia}(s_{ia}^{(3)})}{\pi_{i|a}^{(2)}} \right) = \sum_{i \in s^{(1)}} \frac{1}{\pi_i^{(1)}} \left( \sum_{a \in s_i^{(2)}} \frac{1}{\pi_{i|a}^{(2)}} \left( \sum_{u \in s_{ia}^{(3)}} \frac{y_u}{\pi_{ia|u}^{(3)}} \right) \right)$$

Recall that  $\hat{T}$  is an unbiased estimator of the population total

$$T := \sum_{i \in U^{(1)}} T_i := \sum_{i \in U^{(1)}} \sum_{a \in U_{ia}^{(2)}} T_{ia} := \sum_{i \in U^{(1)}} \sum_{a \in U_i^{(2)}} \sum_{u \in U_{ia}^{(3)}} y_u$$

Let  $\widehat{\text{Var}}[\hat{T}] : \mathcal{S} \rightarrow \mathbb{R}$  be the random variable defined in a recursive manner as follows:

$$\begin{aligned} \widehat{\text{Var}}[\hat{T}](s) &:= \sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\hat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\hat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} + \sum_{i \in s^{(1)}} \frac{\widehat{\text{Var}}[\hat{T}_i](s_i^{(2+)})}{\pi_i^{(1)}} \\ \widehat{\text{Var}}[\hat{T}_i](s_i^{(2+)}) &:= \sum_{a \in s_i^{(2)}} \sum_{b \in s_i^{(2)}} \Delta_{i|ab}^{(2)} \cdot \frac{\hat{T}_{ia}(s_{ia}^{(3)})}{\pi_{i|a}^{(2)}} \cdot \frac{\hat{T}_{ib}(s_{ib}^{(3)})}{\pi_{i|b}^{(2)}} + \sum_{a \in s_i^{(2)}} \frac{\widehat{\text{Var}}[\hat{T}_{ia}](s_{ia}^{(3)})}{\pi_{i|a}^{(2)}} \\ \widehat{\text{Var}}[\hat{T}_{ia}](s_{ia}^{(3)}) &:= \sum_{u \in s_{ia}^{(3)}} \sum_{v \in s_{ia}^{(3)}} \Delta_{ia|uv}^{(3)} \cdot \frac{y_u}{\pi_{ia|u}^{(3)}} \cdot \frac{y_v}{\pi_{ia|v}^{(3)}} \end{aligned}$$

where

$$\begin{aligned} \Delta_{ij}^{(1)} &:= \begin{cases} \pi_i^{(1)} (1 - \pi_i^{(1)}), & \text{if } i = j \\ \pi_{ij}^{(1)} - \pi_i^{(1)} \pi_j^{(1)}, & \text{if } i \neq j \end{cases} \\ \Delta_{i|ab}^{(2)} &:= \begin{cases} \pi_{i|a}^{(2)} (1 - \pi_{i|a}^{(2)}), & \text{if } a = b \\ \pi_{i|ab}^{(2)} - \pi_{i|a}^{(2)} \pi_{i|b}^{(2)}, & \text{if } a \neq b \end{cases} \\ \Delta_{ia|uv}^{(3)} &:= \begin{cases} \pi_{ia|u}^{(3)} (1 - \pi_{ia|u}^{(3)}), & \text{if } u = v \\ \pi_{ia|uv}^{(3)} - \pi_{ia|u}^{(3)} \pi_{ia|v}^{(3)}, & \text{if } u \neq v \end{cases} \end{aligned}$$

Then,  $\widehat{\text{Var}}[\hat{T}]$  is a design-unbiased estimator of the design variance  $\text{Var}[\hat{T}]$  of the  $\hat{T}$ .

### Corollary 2.3

For a three-stage sampling design with invariant and independent subsampling, the fully expanded expression for

$\widehat{\text{Var}}[\widehat{T}]$  is as follows:

$$\begin{aligned}
 \widehat{\text{Var}}[\widehat{T}](s) &:= \sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} + \sum_{i \in s^{(1)}} \frac{\widehat{V}_i(s_i^{(2+)})}{\pi_i^{(1)}} \\
 &= \sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(1)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} \\
 &\quad + \sum_{i \in s^{(1)}} \frac{1}{\pi_i^{(1)}} \left\{ \sum_{a \in s_i^{(2)}} \sum_{b \in s_i^{(2)}} \Delta_{i|ab}^{(2)} \cdot \frac{\widehat{T}_{ia}(s_{ia}^{(3)})}{\pi_{i|a}^{(2)}} \cdot \frac{\widehat{T}_{ib}(s_{ib}^{(3)})}{\pi_{i|b}^{(2)}} + \sum_{a \in s_i^{(2)}} \frac{\widehat{V}_{ia}}{\pi_{i|a}^{(2)}} \right\} \\
 &= \sum_{i \in s^{(1)}} \sum_{j \in s^{(1)}} \frac{\Delta_{ij}^{(1)}}{\pi_{ij}^{(i)}} \cdot \frac{\widehat{T}_i(s_i^{(2+)})}{\pi_i^{(1)}} \cdot \frac{\widehat{T}_j(s_j^{(2+)})}{\pi_j^{(1)}} \\
 &\quad + \sum_{i \in s^{(1)}} \frac{1}{\pi_i^{(1)}} \left\{ \sum_{a \in s_i^{(2)}} \sum_{b \in s_i^{(2)}} \Delta_{i|ab}^{(2)} \cdot \frac{\widehat{T}_{ia}(s_{ia}^{(3)})}{\pi_{i|a}^{(2)}} \cdot \frac{\widehat{T}_{ib}(s_{ib}^{(3)})}{\pi_{i|b}^{(2)}} + \sum_{a \in s_i^{(2)}} \frac{1}{\pi_{i|a}^{(2)}} \left( \sum_{u \in s_{ia}^{(3)}} \sum_{v \in s_{ia}^{(3)}} \Delta_{ia|uv}^{(3)} \frac{y_u}{\pi_{ia|u}^{(3)}} \frac{y_v}{\pi_{ia|v}^{(3)}} \right) \right\},
 \end{aligned}$$

where

$$\begin{aligned}
 \widehat{T}_{ia}(s_{ia}^{(3)}) &= \sum_{u \in s_{ia}^{(3)}} \frac{y_u}{\pi_{ia|u}^{(3)}} \quad \text{and} \quad \widehat{T}_i(s_i^{(2+)}) = \sum_{a \in s_i^{(2)}} \frac{\widehat{T}_{ia}(s_{ia}^{(3)})}{\pi_{i|a}^{(2)}} = \sum_{a \in s_i^{(2)}} \frac{1}{\pi_{i|a}^{(2)}} \left( \sum_{u \in s_{ia}^{(3)}} \frac{y_u}{\pi_{ia|u}^{(3)}} \right) \\
 \Delta_{ia|uv}^{(3)} &:= \begin{cases} \pi_{ia|u}^{(3)} (1 - \pi_{ia|u}^{(3)}), & \text{if } u = v \\ \pi_{ia|uv}^{(3)} - \pi_{ia|u}^{(3)} \pi_{ia|v}^{(3)}, & \text{if } u \neq v \end{cases}
 \end{aligned}$$