

### S3 Appendix - Details of model fitting algorithm.

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**Algorithm 1:** Algorithm to obtain a distribution of calibration parameter sets  $M$  for a single birth cohort.

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**Input:** Equations (12) and (13).  
Parameter distributions  $P(V)$ .  
Calibration parameter prior distributions  $P(M)$ .  
Calibration data in S4 Table and S5 Table.

**Output:** Collection of parameter sets  $\mathcal{S}$ , sampled from  $P(M, V | \mathbf{z})$ .

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1 Initialize  $K_1 \leftarrow 10^4, K_2 \leftarrow 10^6, K_3 \leftarrow 10^6$ 
2 // Stage 1 - Obtain posteriors conditioned on  $V$ 
3 for  $k = 1$  to  $k = K_1$ :
4   Initialize  $c_k \leftarrow 1$ 
5    $V_k \leftarrow$  Sample from  $P(V)$ 
6    $M_{k,1} \leftarrow$  Sample from  $P(M)$ 
7   for  $j = 2$  to  $j = K_2$ : //Start Metropolis-Hastings
8      $M_j \leftarrow$  Sample from proposal distribution  $\rho(M_j | M_{k,c_k})$ 
9      $r \leftarrow$  Sample from Uniform(0,1)
10    if  $a(M_j | M_{k,c_k}) \geq r$ : //  $M_j$  acceptance test (S-1, S3 Appendix)
11       $c_k \leftarrow c_k + 1$  //Update no. accepted parameter sets
12       $M_{k,c_k} \leftarrow M_j$  //Assign accepted sample to  $M_{k,c_k}$ 
13 // Stage 2 - Marginalization over  $V$ 
14 Initialize  $\mathcal{S} \leftarrow \emptyset$ 
15 for  $k = 1$  to  $k = K_3$ :
16    $V_{k^*} \leftarrow$  Sample  $\{V_1, \dots, V_{K_1}\}$  //Sample  $V_{k^*}$  from  $P(V)$ 
17    $M_{k^*,c^*} \leftarrow$  Sample  $\{M_{k^*,c_1}, \dots, M_{k^*,c_k}\}$  //Sample  $M_{k^*,c^*}$  from  $P(M | \mathbf{z}, V_{k^*})$ 
18    $\mathcal{S} \leftarrow \mathcal{S} \cup [V_{k^*}, M_{k^*,c^*}]'$ 

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The Metropolis-Hastings algorithm [7] is implemented in the inner for loop of Algorithm 1. The algorithm is initiated with a vector of calibration parameters  $M = M_1 = [m_{1_1} \ \dots \ m_{1_j}]'$  that is obtained by sampling the prior distributions in Table 1. Next, in the inner loop, the algorithm samples a new vector of calibration parameters  $M_2$  from Table 1 conditional upon  $M_1$ . The probability distribution  $\rho(M_2 | M_1)$  used to propose  $M_2$  when the initial model is  $M_1$  is given by

$$\rho(M_2 | M_1) = \prod_{j=1}^J \rho_j(m_{2_j} | m_{1_j})$$

where  $\rho_j(m_{2_j} | m_{1_j})$  is a normal distribution with a domain limited to the parameter's allowable values.

Once model  $M_2$  is proposed, the algorithm accepts it as the next step in the Markov chain with probability  $a(M_2|M_1)$ . From [7], this acceptance probability is given by

$$a(M_2|M_1) := \min\left(1, \frac{\rho(M_1|M_2)P(M_2|\mathbf{z}, V_k)}{\rho(M_2|M_1)P(M_1|\mathbf{z}, V_k)}\right) \quad \text{S-1}$$

If the model  $M_2$  is accepted, it is appended to the collection of accepted models under the condition  $V = V_k$ . Otherwise  $M_2$  is discarded. A new iteration of the inner loop of Algorithm 1 then begins.