

## SUPPLEMENTARY MATERIAL

### Supplement A: Extended FAST (eFAST) details

#### *Supplement A.1: Choice of sinusoidal function form and choice of frequencies*

In eFAST, partitioning of variance is achieved by encoding the identity of input factors in the frequency of their variation. As explained in the text, the sampling procedure implemented in eFAST defines a sinusoidal function for each input parameter,  $x = f(N_S)$ , that assigns a value to  $x$  based on the number of samples per parameter ( $N_S$ ).

Aside from the requirement that the defining function be sinusoidal, the exact form of function  $f$  depends on the sampling distribution desired for each parameter. Saltelli *et al.* (Saltelli *et al.*, 1999) detail several forms of function  $f$  that result in different parameter distributions (i.e. pdfs).

The frequency of each sinusoidal function  $f$  is critical, as this frequency is used as a parameter identifier to partition variance in later algorithm steps. Frequencies (and their first few harmonics) must be less than the Nyquist critical frequency to avoid aliasing effects. The Nyquist-Shannon sampling theorem defines the Nyquist critical frequency of any discretely sampled signal is equal to 1/2 the sampling frequency. Any frequency component in the signal that exceeds the Nyquist critical frequency is incorrectly aliased to a lower frequency during Fourier analysis. Frequencies must additionally be linearly independent to avoid interference (see (Saltelli *et al.*, 1999) and pages 186-187 of (Saltelli *et al.*, 2000) for details on the choice of frequencies). The collection of one-dimensional sinusoidal functions, one for each input parameter, defines a multi-dimensional search curve that explores many different parameter combinations.

*Supplement A.2: Differences between eFAST and original FAST*

The primary advantage of the eFAST method over the original FAST is the ability to estimate the total-order sensitivity index of each input parameter. The original FAST method assigns a unique frequency to each input parameter, and thus calculates the unique contribution of each parameter in determining the model output. This unique contribution is the first-order sensitivity index,  $S_i$ , as described in the text. To calculate the total-order sensitivity index of a given parameter  $i$ , the eFAST method instead varies  $i$  at a unique, high frequency, but all other parameters at low, not-necessarily unique frequencies. Both FAST and eFAST calculate the first-order  $S_i$  of parameter  $i$  by Fourier analysis, using its unique high frequency. In contrast to FAST, eFAST then calculates the summed sensitivity index of the entire complementary set of parameters (all parameters except  $i$ ). Thus, while FAST partitions variance to each parameter, eFAST partitions variance into two categories: variance due to the parameter of interest  $i$ , and variance due to all other parameters (the complementary set to  $i$ ). Any variance that remains unaccounted for is assumed to be due to non-linear interaction between the parameter of interest and other parameters. The total-order sensitivity index,  $S_{Ti}$ , is then the first-order  $S_i$  plus this remainder fraction of variance, or equivalently, 1 minus the first-order index of the complementary set of parameters:  $S_{Ti} = 1 - (s_{ci}^2 / s_{total}^2)$ . When re-sampling with different parameter search curves (as described above), sensitivity indices are calculated from the mean of re-sampled variances:  $S_i = \text{mean}(s_i^2) / \text{mean}(s_{total}^2)$ .

*Supplement A.3: Determining additivity of a model from eFAST indices*

If  $Y = f(X)$ ,  $X \in \mathbb{R}^k$ , then the model/function  $f$  is additive if  $Y = a_1X_1 + a_2X_2 + \dots + a_kX_k$  and there are no interactions between  $X_i$ . Additivity is a special case of linearity (with

respect to the parameters  $a_i$ ). If interactions between parameters matter in explaining the variability of  $Y$ , then the model  $f$  is not additive. Assuming non-correlated inputs, for additive models the following holds true

$$\sum_{i=1}^k S_i \approx 1 \quad (\text{A.1})$$

Each  $S_i$  delivers a direct measure for the portion of output variance generated by variance in parameter  $i$ , therefore all  $S_i$  should sum to 1. For non-additive models the interactions among the input quantities within the model have to be considered. Equation (A.1) may be used to validate the additivity of a model. Equivalently a comparison between  $S_i$  and  $S_{Ti}$  may lead to a conclusion regarding the additivity of models with non-correlated inputs, namely

$$\begin{aligned} S_{Ti} \approx S_i & \quad \text{ADDITIVE MODEL} \\ S_{Ti} > S_i & \quad \text{NON - ADDITIVE MODEL} \end{aligned} \quad (\text{A.2})$$

Note that equation (A.2) typically does not hold for dynamical systems, because even the simplest solution of an ordinary differential equation entails nonlinearities and interactions<sup>1</sup>.

*Supplement A.4: The total-order index,  $S_{Tdummy}$*

While the artifactually non-zero first-order index,  $S_{dummy}$ , likely derives from aliasing and interference effects, the assignment of a larger artificial value to the total-order index,  $S_{Tdummy}$ , is more complicated. As described in Section 3.3, eFAST estimates the total-order index from the variance unaccounted for after partitioning variance to the parameter of interest and the complementary set of parameters. The remaining variance is assumed

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<sup>1</sup> An alternative way to check for model additivity is to compute the standard regression coefficient (SRC) (see pages 24-27 in Saltelli, A., Chan, K. & Scott, E. M. (2000). *Sensitivity analysis*. Wiley series in probability and statistics, Wiley, Chichester ; New York.), because  $S_i = (\text{SRC}_i)^2$  for additive models.

to be higher-order interactions between the parameter of interest,  $i$ , and other parameters. However, this assumption is imprecise, as interaction between other parameters, but not with the parameter of interest, is included in this remaining variance. For example, given a model with parameters  $i, j$ , and  $k$ , the total-order sensitivity index of parameter  $i$ ,  $S_{Ti}$ , is given by:

$$S_{Ti} = S_i + S_{ij} + S_{ik} + S_{ijk} \quad (\text{A.3})$$

The higher-order terms,  $S_{ij} + S_{ik} + S_{ijk}$ , are approximated by the remaining variance after first-order partitioning. However, this remaining variance includes the interaction between parameters  $j$  and  $k$ ,  $S_{jk}$ . Therefore, by approximating the higher-order interactions of  $i$  using the remaining variance, the interaction effect  $S_{jk}$  is inappropriately included in the total-order index.

*Supplement A.5: Conditions on the two-sample t-test for eFAST  $S_i$  and  $S_{Ti}$*

The two-sample t-test compares two distributions, respectively the first ( $S_i^j$ ) or total-order ( $S_{Ti}^j$ ) sensitivity indexes for the  $k$  inputs/parameters ( $j=1,2,\dots,N_R$ ) with the first or total-order sensitivity indexes of the dummy parameter (i.e. (i.e.,  $S_{dummy}^j$  or  $S_{T_{dummy}}^j$ ,  $j=1,2,\dots,N_R$ )). As described in Section 3.3, the first-order  $S_i^j$  is calculated for each *resampling* ( $N_R$ ) as a fraction of total variance:

$$S_i^j = (s_i^j)^2 / (s_{total}^j)^2, \quad j=1,2,\dots,N_R$$

while  $S_{Ti}$  is calculated as the remaining variance after the contribution of the complementary set,  $S_{c_i}$ , is removed:

$$S_{Ti} = 1 - S_{c_i}$$

The *two-sample t-test* implicitly assumes that

$$\text{mean} \left[ (s_i^j)^2 \right] / \text{mean} \left[ (s_{total}^j)^2 \right] \simeq \text{mean} \left[ (s_i^j)^2 / (s_{total}^j)^2 \right], \quad (\text{A.4})$$

$$i = 1, 2, \dots, k, \quad j = 1, 2, \dots, N_R$$

for the first order coefficients and

$$\text{mean} \left[ (s_{c_i}^j)^2 \right] / \text{mean} \left[ (s_{total}^j)^2 \right] \simeq \text{mean} \left[ (s_{c_i}^j)^2 / (s_{total}^j)^2 \right], \quad (\text{A.5})$$

$$i = 1, 2, \dots, k, \quad j = 1, 2, \dots, N_R$$

for the total order sensitivity coefficients.

Conditions (A.4) and (A.5) can fail due to a large difference in either total variances between different re-samplings ( $s_{total}^j$ , denominators in (A.4) and (A.5)) or in  $s_i^j$  between different resamples. There is no way to control this variability *a priori*. This lack of robustness often occurs because  $N_S$  (the number of samples per parameter per search curve) is too small: the two-sample t-test will likely discard significant  $S_i$  and  $S_{T_i}$ .

We suggest the following method to check for adequacy of the re-sampling. We define the two indexes:

$$\nabla S_i^j = \frac{\text{mean} \left[ (s_i^j)^2 \right] / \text{mean} \left[ (s_{total}^j)^2 \right]}{\text{mean} \left[ (s_i^j)^2 / (s_{total}^j)^2 \right]}, \quad i = 1, 2, \dots, k \text{ and } j = 1, 2, \dots, N_R \quad (\text{A.6})$$

$$\nabla S_{T_i}^j = \frac{\text{mean} \left[ (s_{c_i}^j)^2 \right] / \text{mean} \left[ (s_{total}^j)^2 \right]}{\text{mean} \left[ (s_{c_i}^j)^2 / (s_{total}^j)^2 \right]}, \quad i = 1, 2, \dots, k \text{ and } j = 1, 2, \dots, N_R. \quad (\text{A.7})$$

Coefficients of variation<sup>2</sup> are then calculated on the distributions of (A.6) and (A.7), i.e.

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<sup>2</sup>(CV = (Standard Deviation)/(Mean) =  $\sigma/\mu$ )

$$CV_{\nabla S_i^j} = \frac{\sigma_{\nabla S_i^j}}{\mu_{\nabla S_i^j}} \quad \text{and} \quad CV_{\nabla S_{T_i}^j} = \frac{\sigma_{\nabla S_{T_i}^j}}{\mu_{\nabla S_{T_i}^j}}, \quad i = 1, 2, \dots, k \quad \text{and} \quad j = 1, 2, \dots, N_R \quad (\text{A.8})$$

Comparing the first and total order sensitivity indexes of the  $k$  inputs/parameters with the dummy can be informative, if  $CV_{\nabla S_i^j}$  and  $CV_{\nabla S_{T_i}^j}$  are not too large. We use a threshold of 0.2 and implement the following heuristic conditions

$$\begin{cases} CV_{\nabla S_i} < 0.2 \\ CV_{\nabla S_{T_i}} < 0.2 \end{cases}, \quad i = 1, 2, \dots, k \quad (\text{A.9})$$

Condition (A.9) allows for a variation of 20% around each average value for  $S_i$  and  $S_{T_i}$  across the  $N_R$  resamples). The threshold is a qualitative check on how much variability we allow with the  $S_i$  and  $S_{T_i}$  over different  $N_R$ .

If condition (A.9) is not satisfied for some parameters/inputs, the two-sample t-test results cannot be considered reliable for these parameters/inputs. A way to improve accuracy is to increase  $N_S$ . We implemented a Matlab function (given on website) to check for condition (A.9), where  $CV_{\nabla S_i}$  and  $CV_{\nabla S_{T_i}}$  ( $i = 1, 2, \dots, k$ ) are expressed as percentages for each parameter/input. Unfortunately, when the mean value is near zero (that is the case for many first-order sensitivity indexes  $S_i$ ), the coefficient of variation  $CV_{\nabla S_i}$  is sensitive to change in the standard deviation, limiting its usefulness.

### **Supplement B: Multiple testing corrections for PRCC and eFAST**

Multiple testing corrections adjust p-values derived from multiple statistical tests to correct for occurrence of spurious false positives. The incidence of false positives is proportional to the number of tests performed and the critical significance level (p-value threshold). The total number of statistical tests performed depends on the number of parameters varied and output variables analyzed, but multiple testing corrections are

particularly important when analyzing the output of a dynamical system over many time points. To perform a correction, the p-value of each sensitivity index is multiplied by a correction factor that is a function of the number of tests performed.

Several correction procedures are available. Bonferroni correction (see (Abdi, 2007) for a review) is the most stringent test, providing the most conservative approach to control for false positives. Benjamini and Hochberg False Discovery Rate (Benjamini & Hochberg, 1995) is less stringent and provides a good balance between discovery of statistically significant PRCCs and eFAST indexes and limitation of false positive occurrences. We implement both corrections in our Matlab function for calculating PRCC (see PRCC function online at <http://malthus.micro.med.umich.edu/lab/usanalysis.html>).

A multiple testing correction factor for eFAST is only dependent on  $N_R$  and not on  $N_S$  or  $k^3$ , and, since  $N_R$  is usually within the order of 5-10, there is no need for a correction factor (we use uncorrected p-values for significance testing in comparing eFAST  $S_i$  and  $S_{T_i}$  to the dummy).

If  $\lambda$  is the number of tests performed, the Bonferroni correction multiplies the p-value of each PRCC by  $\lambda$ , namely

$$\text{Corrected } p_i = \lambda p_i, i = 1, \dots, \lambda. \quad (\text{A.10})$$

If the corrected p-value is still below our threshold for significance, then the PRCC is significantly different from 0. Otherwise the PRCC will be considered not significant. For example, if we vary 30 parameters simultaneously in the LHS scheme and check for

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<sup>3</sup> No statistic is known for eFAST sensitivity indexes

significant PRCCs for 5 outputs at 10 different time points, we are looking at a correction factor of  $\lambda = 1500$  (i.e.  $30 \times 5 \times 10$ )<sup>4</sup>.

The Benjamini and Hochberg False Discovery Rate method works in 2 steps. The p-values are first ranked, from the smallest to the largest. The largest p-value remains as is. The second largest p-value is multiplied by the total number of tests  $\lambda$  divided by its rank ( $\lambda - 1$ ). The third p-value is multiplied by  $\lambda$  divided by its rank ( $\lambda - 2$ ). The  $i^{\text{th}}$  largest p-value is then corrected as follows,

$$\text{Corrected } p_i = \left( \frac{\lambda}{\lambda - i + 1} \right) p_i, i = 2, \dots, N. \quad (\text{A.11})$$

### **Supplement C: Log-scale sampling**

If the size of the interval of variation for some parameter is large, values of the parameter in its outer ranges can be neglected during sampling. A way to prevent under-sampling is to sample on a log scale those parameters with large variations. Figure C.1 shows the effect of sampling two parameters,  $s$  and  $\mu_T$ , of the HIV ODE model described in section 4.2. Each point represents a combination of samples of  $s$  and  $\mu_T$  resulting from LHS scheme. Parameters  $s$  and  $\mu_T$  are uniformly sampled in  $[1e^{-2}, 50]$  and  $[1e^{-5}, 0.2]$ , respectively. To prevent under-sampling in the outer ranges, we apply LHS on a log scale if the ratio between the max and the min value of the interval is higher than  $10^3$  (this threshold is arbitrary). We didn't implement the same adjustment in eFAST.

Both  $s$  and  $\mu_T$  exceed this threshold. If a log scale sampling is applied, all regions of the parameter space are sampled at least once (Figure C.1 Panel C). That is not the case if a

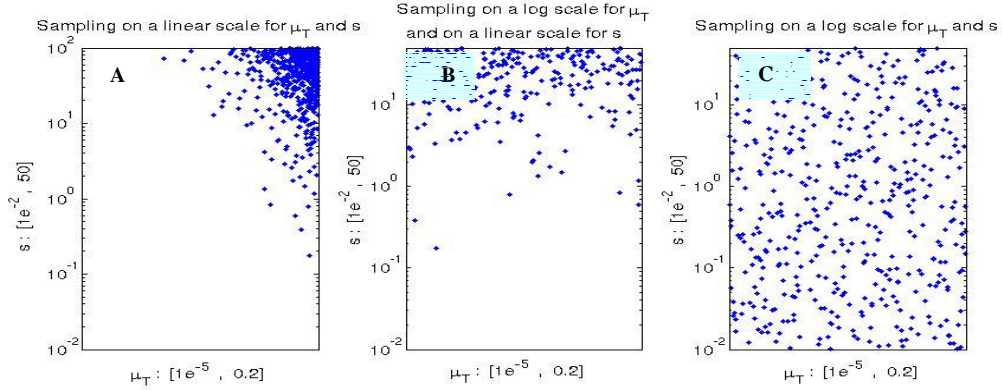
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<sup>4</sup> Equivalently, if the threshold for significance was 5%, the corrected threshold will be 0.000033 (i.e.,  $p/\lambda = 0.05/1500$ ). Each corrected p-value should fall below this new threshold to consider the PRCC significant.



linear scale is implemented: large portions of the parameters space are not sampled (Figure C.1, Panel A and B).

**Figure C.1**

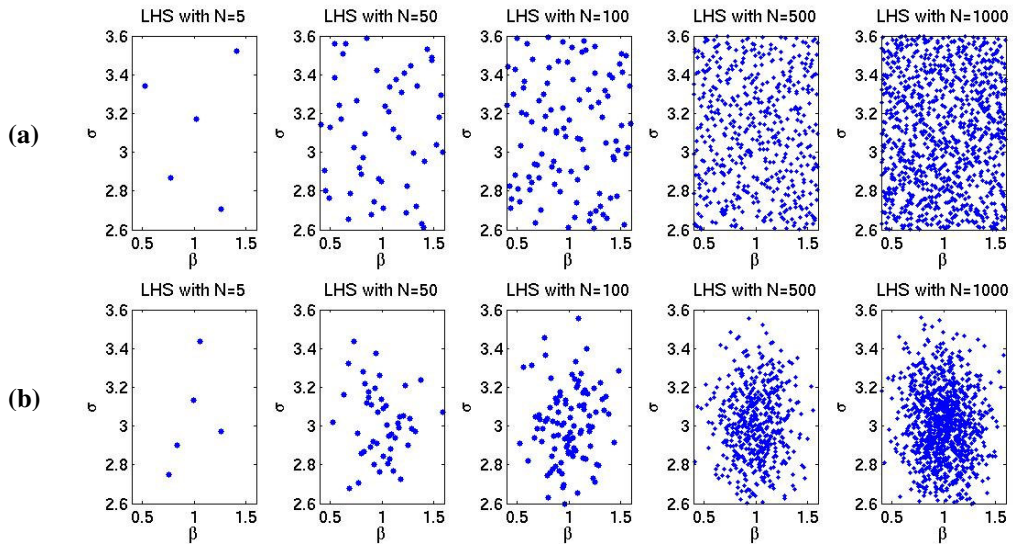


**Figure C.1:** Effect of sampling on linear and log scales in large intervals with a uniform pdf.

**Figure C.2**

LHS schemes for different sample sizes  $N$  applied to the model described by Eqs. (3)-(4)

in the main text.



**Figure C.2:** LHS schemes for different sample sizes  $N$  applied to the model (3)-(4). Parameter  $\beta$  is represented on the abscissa while parameter  $\sigma$  is represented on the ordinate. The plots of row (a) are obtained by using uniform pdfs:  $\beta \in (0.4, 1.6)$  and  $\sigma \in (2.6, 3.6)$ . The plots of row (b) are obtained following Eq. (6) in the main text, namely  $\beta \sim Normal(1, 0.2)$  and  $\alpha \sim Normal(3, 0.2)$ .

## Supplement D: HIV model (Eqs. (15)-(18) in the main text) US analysis results

### PRCC results

**Table D.1:** PRCC results on the HIV-ODE model at 2 different time points (2000 and 4000 days post infection). Ranges for LHS are given in Table II (see main text). Panels A-F show the results for different sample sizes.

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.1068	-0.2490	0.1855	0.4473*	0.6774*	-0.0923	0.7033*	-0.6461*	-0.0284
4000	0.0814	-0.2336	0.1661	0.4281*	0.6761*	-0.0570	0.7009*	-0.6489*	-0.0130

**Panel A:** NS=100

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	-0.1183	-0.3303*	0.0604	0.3374*	0.7698*	0.1621	0.7470*	-0.7529*	0.0453
4000	-0.0939	-0.3306*	0.0427	0.3266*	0.7650*	0.1470	0.7430*	-0.7517*	0.0494

**Panel B:** NS=200

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	-0.0639	-0.3017*	0.0538	0.3981*	0.7194*	-0.0084	0.7254*	-0.6910*	-0.0161
4000	-0.0518	-0.2992*	0.0389	0.4076*	0.7262*	-0.0163	0.7291*	-0.7064*	-0.0032

**Panel C:** NS=300

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	-0.0008	-0.2665*	0.1307*	0.3301*	0.7093*	0.0275	0.6945*	-0.6722*	-0.0366
4000	-0.0082	-0.2671*	0.1247	0.3174*	0.6992*	0.0190	0.6929*	-0.6616*	-0.0490

**Panel D:** NS=400

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0561	-0.2609*	0.0882	0.2996*	0.6772*	0.0041	0.6540*	-0.6932*	-0.0446
4000	0.0627	-0.2616*	0.1012	0.2903*	0.6708*	-0.0084	0.6443*	-0.6889*	-0.0480

**Panel E:** NS=500

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0778	-0.3282*	0.0297	0.3815*	0.6702*	-0.0177	0.6763*	-0.6464*	0.0101
4000	0.0692	-0.3248*	0.0322	0.3865*	0.6739*	-0.0042	0.6824*	-0.6474*	0.0148

**Panel F:** NS=1000

**Table D.2:** Top-Down Coefficient of Concordance (TDCC) for the PRCC results of Panels A-F in Table D.1.

<i>N</i>	<i>TDCC</i>	
	t=2000	t=4000
100-200	0.9169*	0.8987*
200-300	0.991**	0.9647**
300-400	0.9795**	0.9558*
400-500	0.9899**	0.9899**
500-1000	0.973**	0.973**

\*\* : p<0.01, \* : p<0.05

**Table D.3:** PRCC results on the HIV-ODE model at 2 different time points (2000 and 4000 days post infection). Ranges for LHS are given in Table II (see main text). Panels A-F show the results for different sample sizes. Sampling is performed using a log scale if max/min>1e3.

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.1174	-0.4045*	0.1397	0.3132*	-0.0824	0.0794	0.3928*	-0.1826	0.1224
4000	0.1127	-0.5179*	0.1527	0.2854*	-0.0805	-0.1652	0.3357*	-0.2803*	0.0298
<b>Panel A: NS=100</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	-0.054	-0.3425*	0.0329	0.5102*	-0.0886	-0.0015	0.3909*	-0.2128*	-0.0180
4000	-0.065	-0.3826*	-0.0495	0.4049*	0.0427	-0.0384	0.2555*	-0.1777*	-0.0955
<b>Panel B: NS=200</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0091	-0.3071*	0.0404	0.4230*	-0.1330	0.0299	0.3742*	-0.1663*	-0.0343
4000	0.0183	-0.4263*	-0.0042	0.3889*	-0.0427	-0.0451	0.4019*	-0.2099*	-0.1210
<b>Panel C: NS=300</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0026	-0.2481*	0.0746	0.4135*	-0.1060	-0.0000	0.3860*	-0.1793*	-0.0439
4000	0.0354	-0.3616*	0.1604*	0.3962*	-0.1069	0.0133	0.3066*	-0.2564*	-0.0785
<b>Panel D: NS=400</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0874	-0.3290*	-0.0084	0.4210*	-0.1739*	-0.0189	0.4139*	-0.1321*	-0.0216
4000	0.0495	-0.3874*	-0.0077	0.3958*	-0.0466	-0.0214	0.4371*	-0.1928*	-0.0496
<b>Panel E: NS=500</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0160	-0.2991*	0.0286	0.4455*	-0.1394*	-0.0657	0.3650*	-0.2044*	-0.0399
4000	0.0243	-0.4052*	0.0933*	0.3951*	-0.0334	-0.0556	0.3384*	-0.1765*	0.0059
<b>Panel F: NS=1000</b>									

**Table D.4:** Top-Down Coefficient of Concordance (TDCC) for the PRCC results of Panels A-F in Table D.3.

<i>N</i>	<i>TDCC</i>	
	t=2000	t=4000
100-200	0.9728**	0.8621*
200-300	0.9899**	0.9361*
300-400	0.9935**	0.9513*
400-500	0.9550*	0.9412*
500-1000	0.9449*	0.8987*

\*\* : p<0.01, \* : p<0.05

## eFAST results

**Table D.5:** eFAST  $S_i$  and  $S_{Ti}$  results on the HIV-ODE model at 2 different time points (2000 and 4000 days post infection). Ranges for LHS are given in Table II (see main text). Panels A-N show the results for different sample sizes.

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0173	0.0350	0.0482	0.0455	0.0878*	0.0383	0.1145*	0.2676*	0.0456
4000	0.0173	0.0350	0.0481	0.0455	0.0877*	0.0383	0.1145*	0.2676*	0.0456
<b>Panel A: <math>S_i</math> [<math>N_S=65</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.3845	0.5007	0.5535	0.5158	0.6066*	0.4600	0.7098	0.8538*	0.5102
4000	0.3845	0.5008	0.5536	0.5158	0.6067*	0.4601	0.7098	0.8539*	0.5102
<b>Panel B: <math>S_{Ti}</math> [<math>N_S=65</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0325	0.0127	0.0286	0.0293	0.0709*	0.0173	0.0702*	0.3271*	0.0237
4000	0.0325	0.0127	0.0285	0.0293	0.0709*	0.0173	0.0702*	0.3270*	0.0237
<b>Panel C: <math>S_i</math> [<math>N_S=129</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.5347	0.3488	0.4809	0.4766	0.5164	0.4239	0.5321	0.8339*	0.4667
4000	0.5348	0.3488	0.4809	0.4766	0.5164	0.4239	0.5321	0.8339*	0.4667
<b>Panel D: <math>S_{Ti}</math> [<math>N_S=129</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0150	0.0142	0.0284*	0.0242*	0.0753*	0.0229*	0.0776*	0.3232*	0.0184
4000	0.0150	0.0142	0.0284*	0.0240*	0.0753*	0.0229*	0.0776*	0.3232*	0.0184
<b>Panel E: <math>S_i</math> [<math>N_S=257</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.3969	0.3747	0.4872	0.4493	0.5579*	0.4569	0.5734*	0.8480*	0.4222
4000	0.3969	0.3747	0.4872	0.4482	0.5579*	0.4569	0.5736*	0.8480*	0.4224
<b>Panel F: <math>S_{Ti}</math> [<math>N_S=257</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0165	0.0232	0.0207	0.0171	0.0561*	0.0180	0.0739*	0.2796*	0.0177
4000	0.0165	0.0232	0.0207	0.0171	0.0561*	0.0180	0.0739*	0.2796*	0.0178
<b>Panel G: <math>S_i</math> [<math>N_S=513</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.4153	0.4600	0.4425	0.4323	0.4942	0.4443	0.6071*	0.8302*	0.4328
4000	0.4154	0.4600	0.4426	0.4324	0.4943	0.4444	0.6071*	0.8302*	0.4330
<b>Panel H: <math>S_{Ti}</math> [<math>N_S=513</math>]</b>									
<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0018	0.0068*	0.0043*	0.0026*	0.0391*	0.0014	0.0518*	0.1280*	0.0009
4000	0.0018	0.0068*	0.0043*	0.0026*	0.0391*	0.0014	0.0517*	0.1282*	0.0009
<b>Panel I: <math>S_i</math> [<math>N_S=1025</math>]</b>									

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.4693	0.4686	0.4569	0.5047	0.5987*	0.4665	0.5763*	0.8551*	0.4205
4000	0.4688	0.4687	0.4570	0.5047	0.5988*	0.4665	0.5764*	0.8551*	0.4205

**Panel L:**  $S_{Ti}$  [ $N_S=1025$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0012	0.0042*	0.0031*	0.0017	0.0352*	0.0010	0.0487*	0.1974*	0.0005
4000	0.0012	0.0042*	0.0031*	0.0017	0.0352*	0.0010	0.0487*	0.1975*	0.0005

**Panel M:**  $S_i$  [ $N_S=2049$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.4181	0.4308	0.4412	0.4603	0.5894*	0.4568	0.5583*	0.8445*	0.4173
4000	0.4182	0.4309	0.4414	0.4603	0.5894*	0.4569	0.5584*	0.8445*	0.4173

**Panel N:**  $S_{Ti}$  [ $N_S=2049$ ]

**Table D.6:** Coefficient of Variations described in Supplement A.5 for  $S_i$  and  $S_{Ti}$  results across the resamples ( $N_R$ ) on the HIV-ODE model at 2 different time points (2000 and 4000 days post infection). Panels A-N show the results for different sample sizes.

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	27.6270	50.6562	85.8384	65.6931	40.4772	110.8997	55.5056	19.5493	50.7581
4000	27.6332	50.6821	85.8076	65.4197	40.3326	111.0496	55.5066	19.5538	50.8285

**Panel A:** Coefficients of Variation for  $S_i$  [ $N_S=65$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	32.3344	18.9849	8.4448	14.4363	18.4949	15.7540	21.4101	5.3203	9.8655
4000	32.3339	18.9785	8.4263	14.4369	18.3964	15.7751	21.4030	5.3098	9.8863

**Panel B:** Coefficients of Variation for  $S_{Ti}$  [ $N_S=65$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	66.4009	37.1084	47.1681	38.8312	42.9006	57.7603	20.8953	7.5438	68.7373
4000	66.4141	37.6689	47.0853	38.8305	42.8930	57.8376	20.8835	7.5592	68.6892

**Panel C:** Coefficients of Variation for  $S_i$  [ $N_S=129$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	19.4592	33.4483	13.2410	17.4296	20.7016	20.5410	11.0773	3.1447	33.7744
4000	19.4569	33.6302	13.2481	17.4266	20.7030	20.5229	11.0739	3.1448	33.7709

**Panel D:** Coefficients of Variation for  $S_{Ti}$  [ $N_S=129$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	75.6668	68.2531	10.8336	24.5938	15.5854	14.3132	3.1165	6.1560	15.3970
4000	75.4665	68.2950	10.9324	25.2706	15.6287	14.1029	3.0968	6.1630	15.4647

**Panel E:** Coefficients of Variation for  $S_i$  [ $N_S=257$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	22.8305	23.2808	6.1407	11.2132	11.5687	10.4057	9.7493	2.7791	14.3156
4000	22.7958	23.2928	6.1285	11.4409	11.5712	10.3824	9.7243	2.7704	14.3153

**Panel F:** Coefficients of Variation for  $S_{Ti}$  [ $N_S=257$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N$	$\mu_V$	<i>dummy</i>
2000	29.6937	52.7933	46.3433	6.6893	5.4713	25.2698	14.1906	12.9174	17.6040
4000	29.8846	52.8598	46.4226	6.6961	5.4463	25.2115	14.1742	12.9181	17.4123

**Panel G:** Coefficients of Variation for  $S_i$  [ $N_S=513$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	7.6933	15.6349	13.3265	14.7151	7.0411	8.4665	9.3695	1.2625	12.2550
4000	7.6836	15.6336	13.3108	14.7121	7.0351	8.4625	9.3634	1.2611	12.2753

**Panel H:** Coefficients of Variation for  $S_{Ti}$  [ $N_S=513$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	44.7893	42.0246	15.8155	40.2886	25.0616	86.3381	7.9166	40.1370	38.4888
4000	44.4671	42.0021	15.4814	40.4222	25.0753	86.2653	7.9596	40.1090	38.6360

**Panel I:** Coefficients of Variation for  $S_i$  [ $N_S=1025$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	11.9433	13.4549	3.0501	16.5545	5.9074	15.8635	4.0985	2.0700	8.6099
4000	11.8901	13.4592	3.0460	16.5575	5.8910	15.8596	4.0905	2.0663	8.6110

**Panel L:** Coefficients of Variation for  $S_{Ti}$  [ $N_S=1025$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	74.8358	23.0827	39.6820	67.2312	22.1101	64.9453	9.6696	26.3278	25.0941
4000	75.3972	22.7410	39.4439	67.1669	22.1482	64.7345	9.6436	26.4074	25.0236

**Panel M:** Coefficients of Variation for  $S_i$  [ $N_S=2049$ ]

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	7.1642	4.8226	3.4069	8.5539	6.4335	12.9741	2.4695	1.4821	4.6299
4000	7.1603	4.7716	3.3939	8.5593	6.4554	12.9718	2.4682	1.4784	4.6285

**Panel N:** Coefficients of Variation for  $S_{Ti}$  [ $N_S=2049$ ]

**Table D.7:** Top-Down Coefficient of Concordance (TDCC) for eFAST  $S_i$  and  $S_{Ti}$  results of Panels A-N in Table D.5 and D.6.

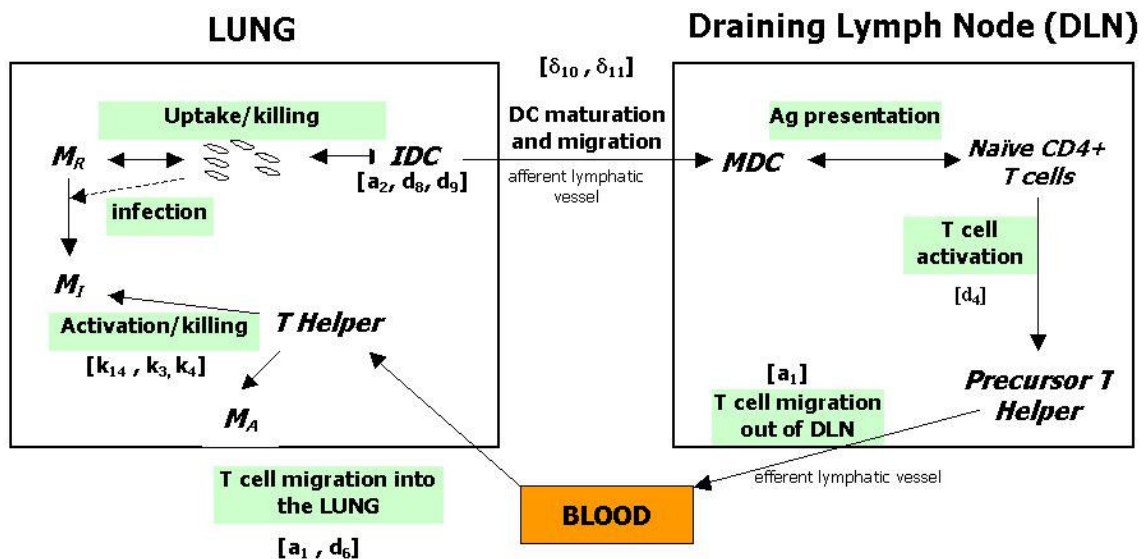
<i>N</i>	<i>TDCC - S<sub>i</sub></i>		<i>TDCC - S<sub>Ti</sub></i>	
	t=2000	t=4000	t=2000	t=4000
65-129	0.4239	0.4239	0.2518	0.2518
129-257	0.7906*	0.7906*	0.6922*	0.6922*
257-513	0.3882	0.3882	0.4239	0.4239
513-1025	0.5229	0.5229	0.2290	0.2290
1025-2049	1**	1**	0.8121*	0.8121*

\*\* :  $p < 0.01$ , \* :  $p < 0.05$

## Supplement E: Two compartmental ODE model of *M. tuberculosis* infection

### Supplement E.1: Model description

To capture global dynamics of Mtb infection and immunity, we developed a two compartmental mathematical model (Marino & Kirschner, 2004; Marino *et al.*, 2004) that extended on a previous model (Wigginton & Kirschner, 2001) and that qualitatively and quantitatively addresses important processes of cellular priming and activation. These processes occur between the site of infection (lung) and the nearest draining lymph node (DLN) (see Figure E.1). The key cells mediating this process are the dendritic cells (DC). The ODE model describes the dynamics of macrophages (resting [MR], infected [MI] and activated [MA]), dendritic cells (immature [IDC] and mature [MDC]), lymphocytes (Naïve CD4+ T cells in the lymph node [T], Th0 in the lung [T0] and in the lymph node [T0LN], Th1 [T1] and Th2 [T2] in the lung), bacteria (intracellular [BI] and extracellular [BE]) and cytokines (IFN $\gamma$ , IL12 in the lung and in the lymph node [IL12LN], IL10 and IL4).



**Figure E.1:** diagram of the main processes (uptake, trafficking and presentation) described in the two compartmental ODE model of *M. tuberculosis* infection in humans.

During infection, macrophages are the prime target cells for Mtb. However, upon activation, macrophages can both kill intracellular bacteria and participate in a protective T helper cell type 1 (Th1) response (targeting intracellular bacteria). Immature or resting DCs (IDC) are present at sites of infection (such as the lung) at the onset of the inflammatory response: they are specialized for antigen uptake, processing and presentation. After bacterial uptake, immature DCs differentiate into the mature phenotype (mature DC or MDC) and migrate through the afferent lymphatic vessels into T cell area of the closest draining lymph node (DLN), where they perform two main functions: naive T cell recruitment and antigen presentation. Once presentation occurs, naive T cells experience stages of differentiation from naive to armed effector T cell. This phenotypic and functional change allows primed T cells to proliferate and migrate through the efferent lymphatic vessels into the blood, and eventually into the site of infection. As professional antigen presenting cells (APCs), dendritic cells play a major role in establishing an effective adaptive response.

**Table E.1**

**Table E.1:** parameter definitions and values of the two-compartmental model

<i>Parameter</i>	<i>Description</i>	<i>Range</i>
$\xi$	fraction of Th0 migrating out of the DLN into the blood	[1e-4 , 1]
$\delta_{10}$	Max rate of IDC activation/maturation/migration from the lung to the DLN	[1e-4 , 1]
$s_{IDC}$	IDC baseline turnover in the lung	[1 , 1e3]
$k_2$	Max infection rate of macrophages due to $B_E$	[1e-4 , 1]
$k_3$	Max activation rate of macrophages induced by $B_T$ and $IFN\gamma$	[1e-3 , 1]
$k_4$	Max deactivation rate of macrophages induced by IL10	[1e-3 , 1]
$k_{14}$	Max rate of infected macrophage killing by T cells (apoptosis, CTL)	[1e-3 , 1]
$\delta_4$	Rate of MDC-T cell interaction (antigen presentation, T cell activation)	[1e-7 , 1e-1]
$\delta_8$	Mx rate of recruitment of IDC due to $B_E$	[1e-4 , 1e-1]
$\delta_6$	Half saturation of Th0 migration from the LN due to $M_A$	[1e3 , 1e5]
$\delta_9$	Half saturation of IDC recruitment due to $B_E$	[1e5 , 1e6]
$\delta_{11}$	Half saturation of IDC activation/maturation/migration due to $B_E$	[1e3 , 1e5]



**Supplement E.2: Two compartmental model US analysis results**

**PRCC results**

NS=100												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.0288	-0.2527	-0.2871*	-0.1726	0.0174	0.1652	-0.1503	-0.0553	-0.1187	-0.0803	0.0287	0.0305	-0.0575
-0.1112	0.2113	-0.5448*	0.8755*	-0.4074*	0.4129*	-0.3075*	-0.1265	-0.0136	-0.1145	-0.0072	0.0565	-0.0002
-0.0329	0.5810*	-0.3106*	0.7968*	-0.5358*	0.3557*	-0.2027	-0.1959	0.0887	-0.0061	0.0945	0.1024	-0.0720
MDC												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0473	0.9697*	0.7086*	-0.5004*	0.0350	0.0794	-0.0129	-0.0137	-0.0564	-0.0918	0.0258	0.1301	0.1428
0.0773	0.2145	0.7082*	0.5647*	0.0740	0.1069	-0.1255	-0.0906	-0.0438	-0.0005	0.1584	0.1483	-0.1085
0.0644	-0.2188	0.4983*	0.5502*	-0.0295	0.2229	-0.1491	-0.1134	-0.0024	0.0244	0.1249	0.2154	-0.1403
Th1												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.8935*	0.8926*	0.3152*	0.4978*	0.8546*	0.0645	0.0804	0.1441	-0.0860	0.0599	-0.0246	-0.0957	0.1302
0.6717*	-0.1464	0.0647	0.4719*	0.6747*	-0.2161	-0.1560	0.0909	-0.0204	-0.0851	-0.0418	0.1090	-0.0357
0.6648*	-0.3083*	-0.0530	0.0234	0.7082*	-0.0317	-0.2508*	0.0848	0.0494	-0.1420	0.0096	0.2379	-0.1415
NS=200												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.0032	0.0476	-0.0422	-0.1835	0.0409	0.1739	-0.1537	-0.1484	0.0696	-0.0286	0.0014	-0.0926	0.0588
0.0411	0.3094*	-0.4387*	0.8558*	-0.4713*	0.3707*	-0.1311	-0.0488	-0.0123	0.0164	-0.0935	-0.0569	0.0587
0.0533	0.5821*	-0.4043*	0.6861*	-0.4651*	0.2717*	-0.0486	-0.0221	0.0223	0.0469	0.0563	-0.0787	-0.0387
MDC												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0307	0.9739*	0.7725*	-0.5695*	-0.0116	0.1179	-0.0499	-0.0985	0.1782	0.0620	0.0361	-0.2093	0.0434
-0.0479	0.3963*	0.7519*	0.5351*	-0.0070	0.0447	-0.1630	-0.0120	-0.0261	-0.0772	0.0295	-0.0314	0.1033
-0.1284	-0.1303	0.5146*	0.5168*	-0.1402	0.1082	-0.0781	-0.0161	-0.0220	-0.0470	0.0690	0.0532	0.1410
Th1												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.8828*	0.9129*	0.4627*	0.4052*	0.8457*	0.1211	-0.0848	0.0317	0.1352	-0.0772	-0.0621	-0.1629	-0.0199
0.4930*	0.1820	0.1813	0.3929*	0.6039*	-0.0679	-0.1817	-0.0828	0.0271	-0.0418	0.0643	-0.0398	0.1080
0.4967*	0.0377	0.0284	0.0506	0.5652*	-0.0310	-0.1891*	-0.0646	-0.0050	-0.0535	0.0941	-0.0055	0.1266

NS=300												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.0978	0.9705*	0.7542*	-0.5362*	0.0569	0.1371	-0.0484	0.0079	-0.0590	-0.0046	0.0170	-0.0600	-0.0862
-0.0787	0.3343*	0.7292*	0.5789*	-0.1841*	0.1350	-0.0528	-0.0428	-0.0364	-0.0475	0.0638	-0.0924	-0.0666
-0.1798*	-0.1636*	0.5515*	0.5634*	-0.3815*	0.1713	-0.0521	-0.0446	0.0015	-0.0716	0.0446	-0.0815	-0.1135
MDC	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0910	0.9734*	0.7598*	-0.5324*	0.0890	-0.0896	-0.0046	-0.0923	0.0460	0.0202	0.0327	-0.0864	0.0317
-0.0581	0.3947*	0.7689*	0.5894*	-0.0499	-0.0166	-0.1261	-0.0186	0.0600	0.0502	0.0305	-0.0204	0.0779
-0.0325	-0.0969	0.4821*	0.5090*	-0.2422*	0.1244	-0.1788*	-0.0225	0.0391	0.0482	-0.0397	-0.0133	0.0601
Th1	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.8821*	0.8988*	0.3888*	0.4183*	0.8373*	0.0650	-0.0418	0.1135	-0.0490	0.0110	0.0307	-0.0821	-0.1077
0.5534*	0.0429	0.0760	0.3930*	0.5320*	-0.0701	-0.1083	-0.0411	-0.0554	-0.1096	0.0732	-0.0520	-0.0175
0.4803*	-0.1662*	-0.0067	0.0062	0.4375*	-0.0557	-0.1299	-0.0557	-0.0699	-0.0816	0.0492	-0.0442	-0.0239
NS=400												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.0672	0.1071	-0.1235	-0.1941*	-0.0483	-0.1802*	0.0327	0.0536	0.0076	-0.1222*	0.0125	0.0037	-0.0479
0.0142	0.2545*	-0.4485*	0.8459*	-0.5470*	0.1379*	-0.0838	0.0892	0.1296*	-0.0349	-0.0165	0.0032	-0.0443
-0.0272	0.4781*	-0.3343*	0.6001*	-0.4952*	0.1454*	-0.0686	0.0382	0.0603	-0.0089	0.0368	0.0280	-0.0413
MDC	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0036	0.9717*	0.7328*	-0.4922*	-0.0418	-0.1095	0.0307	0.0233	0.0154	-0.1027	0.0842	-0.0637	-0.0245
0.0985	0.3976*	0.7569*	0.6085*	-0.1616*	-0.0604	0.0434	0.0008	-0.0800	-0.0076	-0.0240	0.0573	-0.0336
0.1015	-0.1574*	0.5639*	0.5868*	-0.2869*	0.0108	0.0520	-0.0105	-0.0190	-0.0140	-0.0322	0.0161	-0.0478
Th1	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.8751*	0.9012*	0.3870*	0.4323*	0.8179*	-0.1204	0.0348	0.1054	-0.0128	-0.0987	-0.0160	-0.0437	-0.0304
0.5752*	0.1257	0.1656*	0.3969*	0.5593*	-0.3174*	0.0166	0.0148	0.0138	-0.0572	0.0070	0.0322	-0.0791
0.5925*	-0.0649	0.0567	-0.0065	0.5235*	-0.2865*	-0.0384	0.0041	-0.0424	-0.0460	-0.0279	0.0334	-0.1135

NS=500												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0063	-0.0087	-0.1826*	-0.1938*	0.0067	0.0049	0.0589	0.0252	-0.0348	0.0031	0.0470	-0.0255	-0.0390
-0.2141*	0.2555*	-0.5394*	0.8418*	-0.5091*	0.1987*	-0.0787	-0.0577	0.0266	-0.0157	-0.0328	-0.0012	-0.0739
-0.1739*	0.5272*	-0.4131*	0.6594*	-0.4778*	0.1530*	-0.0670	-0.0586	0.0565	-0.0610	-0.0139	0.0052	-0.0930
MDC												
	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0265	0.9693*	0.7188*	-0.5094*	-0.0271	0.0439	-0.0405	0.0404	-0.0148	-0.0232	0.0125	-0.0560	-0.0322
-0.0444	0.3627*	0.7366*	0.5786*	-0.0175	0.0615	-0.0162	0.0066	0.0102	-0.0327	-0.0542	-0.0343	0.0490
-0.1063*	-0.1749*	0.5335*	0.5132*	-0.1337*	0.1263*	-0.0905	0.0063	0.0162	-0.1128*	-0.0774	-0.0164	0.0310
Th1												
	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.8768*	0.8927*	0.3556*	0.4163*	0.8309*	0.0257	-0.0245	0.1581*	-0.0438	-0.0134	0.0235	-0.0368	-0.0074
0.5247*	0.0368	0.1328*	0.4271*	0.5842*	-0.1945*	-0.0169	0.0760	-0.0036	-0.0072	-0.0289	-0.0209	0.0384
0.4626*	-0.1195*	0.0637	0.0354	0.5097*	-0.1110	-0.1495*	0.0650	0.0166	-0.0585	-0.0547	-0.0346	0.0661
NS=1000												
BE	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0412	-0.0241	-0.1127*	-0.2011*	-0.0329	0.0022	-0.0956*	0.0129	0.0156	0.0297	-0.0224	-0.0125	0.0048
-0.0460	0.3066*	-0.4712*	0.8710*	-0.5564*	0.2779*	-0.1088*	0.0119	0.0553	0.0351	-0.0293	-0.0409	-0.0548
-0.1133*	0.5516*	-0.2826*	0.6612*	-0.4824*	0.2119*	-0.1119*	0.0106	0.0819*	0.0102	0.0079	0.0295	-0.0613
MDC												
	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
-0.0316	0.9693*	0.7344*	-0.5096*	-0.0129	-0.0155	-0.0858*	0.0004	0.0420	0.0243	0.0255	0.0030	-0.0060
0.0100	0.3811*	0.7671*	0.5668*	-0.0875*	0.0294	-0.0607	0.0351	0.0415	0.0107	-0.0914*	0.0416	-0.0335
0.0030	-0.1388*	0.5765*	0.5322*	-0.1837*	0.1277*	-0.0974*	0.0421	0.0628	0.0535	-0.0805	0.0576	-0.0520
Th1												
	=											
$\xi$	$\delta_{10}$	$s_{IDC}$	$k_2$	$k_3$	$k_4$	$k_{14}$	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	<i>dummy</i>
0.8737*	0.8942*	0.4219*	0.4409*	0.8239*	-0.0368	-0.1072*	0.1086*	0.0594	-0.0088	0.0352	0.0145	0.0179
0.4676*	0.0671	0.1916*	0.3987*	0.5462*	-0.1441*	-0.0582	0.0396	0.0268	0.0130	-0.0169	0.0145	-0.0049
0.4496*	-0.0688	0.0930*	0.0269	0.4974*	-0.1072*	-0.1484*	0.0174	0.0406	0.0305	-0.0183	0.0354	-0.0542

**TOP-DOWN COEFFICIENT OF CONCORDANCE (TDCC) for LHS\PRCC**

*BE*

<i>N</i>	<b>TDCC</b>		
	t=100	t=500	t=1000
100-200	0.2569	0.8067**	0.8818**
200-300	0.7295*	0.8968**	0.908**
300-400	0.6209*	0.9417**	0.9697**
400-500	0.6526*	0.8006**	0.958**
500-1000	0.6168*	0.8567**	0.9863**

\*\*:*p*<0.01, \*:*p*<0.05

*MDC*

<i>N</i>	<b>TDCC</b>		
	t=100	t=500	t=1000
100-200	0.5334	0.6447*	0.4984
200-300	0.6987*	0.2876	0.867***
300-400	0.5949*	0.5794	0.6866*
400-500	0.6247*	0.0354	0.6456*
500-1000	0.7381*	0.7*	0.7658*

\*\*:*p*<0.01, \*:*p*<0.05

*Th1*

<i>N</i>	<b>TDCC</b>		
	t=100	t=500	t=1000
100-200	0.7551*	0.5521**	0.304
200-300	0.5981*	0.6749*	0.5083
300-400	0.3981	0.7219*	0.3853
400-500	0.3296	0.7219*	0.3853
500-1000	0.4317	0.8854**	0.8487**

\*\*:*p*<0.01, \*:*p*<0.05

*Supplement E.3: Two compartmental model: eFAST results*

Extracellular Bacteria – BE [N<sub>S</sub>=65]

Si\_BE\_65

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.0038	0.0067*	0.0044	0.3244*	0.0057	0.0034	0.0053	0.0064*	0.0033	0.0051	0.0034	0.0060	0.0026
0.0895	0.0265	0.0460	0.0585*	0.0513	0.0572	0.2289*	0.0103	0.0051	0.0051	0.0069	0.0080	0.0098
0.0880	0.0513	0.0652*	0.0661*	0.1561*	0.0574	0.1071*	0.0097	0.0041	0.0075	0.0108	0.0125	0.0047

CVsi\_BE\_65

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
86.8628	38.3861	63.8279	6.0697	91.9956	96.7852	77.9249	36.2095	90.4711	44.6985	48.5835	80.9546	53.7108
100.3436	49.1524	51.3573	45.4020	60.0721	72.5628	17.8410	105.5258	188.2265	100.8178	119.0568	64.7040	77.6912
90.4884	88.2778	30.7078	46.0177	49.7105	78.5018	41.0348	143.7117	168.7495	129.8468	80.9908	139.7135	123.5859

Sti\_BE\_65

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.6966	0.6979	0.6684	0.9924*	0.6532	0.6502	0.6679	0.6813	0.6812	0.6932	0.6552	0.6452	0.6570
0.4895	0.3602	0.4892	0.5421	0.4402	0.5016	0.7138*	0.3584	0.3394	0.3887	0.2918	0.3850	0.3300
0.5292	0.4401	0.5130	0.5666	0.6195	0.4450	0.5546	0.2966	0.3311	0.3199	0.3036	0.3296	0.2899

CVsti\_BE\_65

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
7.3302	3.4523	6.0620	0.4939	4.6133	3.9000	3.5900	3.9193	6.3403	7.5275	6.9258	5.0233	5.7635
42.5563	25.8821	29.7230	27.1947	26.3716	28.4626	11.1503	32.4773	44.1996	29.4062	22.7306	25.6159	28.2485
43.9069	40.4246	27.7896	35.4428	17.3258	35.7115	17.5528	52.5841	49.0303	45.9448	39.8224	45.1248	37.9895

Mature Dendritic Cells – MDC [N<sub>S</sub>=65]

Si\_MDC\_65 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.1099*	0.1097*	0.0585*	0.0431*	0.1596*	0.0017	0.0041	0.0029	0.0025	0.0032	0.0030	0.0013	0.0032
0.0818*	0.0083	0.0436	0.0221	0.0354	0.0258	0.2760*	0.0094	0.0198	0.0133	0.0065	0.0153	0.0202
0.0917*	0.0186	0.0430	0.0244	0.0523	0.0302	0.2642*	0.0215	0.0328	0.0161	0.0129	0.0180	0.0293

CVsi\_MDC\_65 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
140.8227	18.0515	34.6070	9.5636	148.8631	49.9253	95.3691	80.6727	148.9018	66.9880	122.7160	66.3718	45.7464
74.7551	152.9174	18.4005	48.1771	122.2057	131.3604	15.8268	80.3923	94.1299	89.4211	96.0603	70.4982	89.7999
77.0756	120.9874	18.6690	27.4835	130.6108	125.4884	13.7963	69.3100	94.2891	87.4892	80.4512	101.5912	67.5134

Sti\_MDC\_65 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.7020	0.6689	0.5494	0.5468	0.7255	0.4841	0.4749	0.5452	0.5065	0.4791	0.5014	0.4573	0.6384
0.6080*	0.3872	0.4990	0.4732	0.5106	0.4600	0.8318*	0.3532	0.4300	0.4146	0.4302	0.3989	0.4613
0.5906	0.4078	0.4845	0.4627	0.4921	0.4855	0.8067	0.4081	0.4775	0.4496	0.4171	0.4160	0.4939

CVsti\_MDC\_65 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
28.2544	11.0587	20.4799	9.1491	14.6956	21.2334	21.1512	28.6563	20.0182	17.4426	27.1018	18.9809	22.3807
8.3302	13.0828	5.3871	9.9565	25.5803	19.3074	4.6418	8.2433	13.7049	13.6389	10.1435	12.7780	8.4518
8.0963	24.1285	4.8032	7.5875	27.6128	19.3176	4.6295	10.4173	13.6230	13.2465	8.3126	20.4179	7.9913

T Helper cells type I – Th1 [N<sub>S</sub>=65]

Si\_TH1\_65 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.0055	0.1358*	0.0976*	0.2056*	0.0029	0.0007	0.0027	0.0061	0.0048	0.0017	0.0026	0.0009	0.0011
0.0102	0.0052	0.1113*	0.0100	0.0259	0.0044	0.3187*	0.0049	0.0035	0.0088	0.0065	0.0025	0.0071
0.0142	0.0456	0.1045*	0.0216	0.0273	0.0069	0.3227*	0.0093	0.0065	0.0129	0.0094	0.0079	0.0125



T Helper cells type I – Th1 [N<sub>s</sub>=129]

Si\_TH1\_129 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.0008	0.1248*	0.1070*	0.2073*	0.0014	0.0010	0.0014	0.0012	0.0008	0.0013	0.0012	0.0016	0.0014
0.0082	0.0032	0.1134*	0.0069	0.0183	0.0011	0.3074*	0.0016	0.0009	0.0033	0.0025	0.0026	0.0028
0.0215	0.0434	0.1036*	0.0147	0.0168	0.0020	0.3283*	0.0032	0.0020	0.0082	0.0042	0.0043	0.0039

CVsi\_TH1\_129 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
15.1347	12.7960	31.4362	27.3040	7.3869	80.1214	71.9512	69.4527	93.3157	83.1985	71.1344	60.7786	81.4784
19.4860	90.8395	29.1228	90.1381	56.4234	58.5268	9.5870	80.8807	93.6591	62.5016	40.8374	52.7626	80.2078
16.7164	87.5921	28.7937	47.4236	30.3210	68.1802	11.3491	58.3934	58.2101	66.9167	72.3731	71.4664	28.9149

Sti\_TH1\_129=

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.4724	0.6343*	0.6347*	0.7409*	0.4650	0.4558	0.5004	0.4910	0.5851*	0.4687	0.4677	0.4285	0.5069
0.4759	0.5048	0.6530*	0.4791	0.5126	0.4539	0.8484*	0.4399	0.4374	0.4671	0.4300	0.4588	0.4805
0.5303	0.6984	0.6518*	0.4923	0.5083	0.4397	0.8603*	0.4327	0.4232	0.4845	0.4277	0.4453	0.4699

CVsti\_TH1\_129 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
11.6624	10.5610	7.4554	19.7504	6.1796	19.5978	11.3739	15.5800	16.2055	10.2638	3.4555	16.0248	19.0006
5.8117	20.7312	8.2141	18.8029	21.3050	25.7691	5.0402	10.5850	13.6532	12.6350	26.6565	8.0826	14.4674
9.1898	15.3408	10.7155	17.4915	14.0927	20.7839	3.8248	17.7457	15.3558	18.6097	26.7293	12.9438	16.6652

Extracellular Bacteria – BE [N<sub>s</sub>=257]

Si\_BE\_257 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.0025	0.0023	0.0038*	0.3283*	0.0025	0.0025	0.0031	0.0022	0.0024	0.0024	0.0024	0.0024	0.0022
0.0473*	0.0070*	0.0231*	0.0360*	0.0673*	0.0138*	0.3179*	0.0021	0.0015	0.0007	0.0013	0.0025	0.0021
0.0236	0.0165*	0.0371*	0.0330*	0.1752*	0.0181*	0.1250*	0.0017	0.0020	0.0006	0.0006	0.0019	0.0046

CVsi\_BE\_257 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
18.1510	19.1695	24.8259	1.1347	17.4597	9.4464	15.1906	5.8681	14.9833	18.9544	11.1743	7.0221	13.3638
25.1515	53.5338	31.3204	21.1334	51.9089	34.6328	11.2448	89.2002	46.6025	91.7668	122.3768	42.7518	32.7818
89.4831	55.0413	63.2962	43.4050	38.1521	50.5633	31.7924	149.7740	109.8429	86.9036	105.0679	104.2631	69.9682

Sti\_BE\_257 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.6602	0.6652	0.6669	0.9930*	0.6569	0.6605	0.6611	0.6526	0.6588	0.6652	0.6605	0.6569	0.6552
0.4302*	0.3148	0.3390	0.4048*	0.4423*	0.3515	0.7636*	0.3118	0.3466	0.2637	0.2761	0.3208	0.3307
0.3198	0.2838	0.3364	0.3547	0.6694*	0.2537	0.5411*	0.2520	0.2774	0.1882	0.2068	0.2356	0.3518

CVsti\_BE\_257 =

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.6900	0.4750	2.2779	0.1909	0.7701	1.2718	1.0400	1.1780	2.2386	0.9957	1.0241	1.8233	1.8169
8.2341	8.9253	12.8443	5.2754	23.7513	7.7154	7.4213	17.8793	19.6273	14.4308	33.1798	21.1381	17.1012
40.1390	20.8303	36.6597	29.6766	17.3137	30.4705	15.7334	47.1933	42.4482	35.5814	24.2164	34.6719	22.2617

Mature Dendritic Cells – MDC [N<sub>s</sub>=257]

Si\_MDC\_257=

$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy
0.0900*	0.0904*	0.0642*	0.0442*	0.1370*	0.0018	0.0030	0.0016	0.0017	0.0022	0.0017	0.0020	0.0017
0.0759*	0.0017	0.0253*	0.0117*	0.0263*	0.0334*	0.2512*	0.0012	0.0021	0.0010	0.0022	0.0021	0.0019
0.0724*	0.0030	0.0264*	0.0306*	0.0359*	0.0337*	0.2489*	0.0036	0.0030	0.0022	0.0031	0.0031	0.0020











CVsi_TH1_2049	=												
$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy	
2.9282	2.7043	9.3585	8.7888	7.6713	58.5010	39.3522	72.5307	87.0483	46.9633	64.9113	86.2110	57.5326	
3.3498	32.7506	5.0565	17.0554	9.5987	20.9087	2.8226	105.7453	76.7754	83.7016	112.6700	108.4503	66.3897	
11.0960	53.4468	15.7020	21.1009	11.0417	31.2374	8.0302	65.1240	76.9203	69.4582	63.3900	62.5416	109.1498	

Sti_TH1_2049	=												
$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy	
0.3978	0.6401*	0.5934*	0.7372*	0.3918	0.3964	0.4069	0.4122*	0.4036*	0.4073*	0.4021	0.4011	0.3838	
0.4253*	0.4067	0.6265*	0.4072	0.4211*	0.3963	0.8477*	0.3967	0.3886	0.3946	0.3988	0.3879	0.3951	
0.4130	0.4165	0.6031*	0.4152	0.4061	0.4165	0.8499*	0.3932	0.3787	0.3836	0.3877	0.3809	0.3979	

CVsti_TH1_2049	=												
$\xi$	$\delta_{10}$	S <sub>IDC</sub>	k <sub>2</sub>	k <sub>3</sub>	k <sub>4</sub>	k <sub>14</sub>	$\delta_4$	$\delta_8$	$\delta_6$	$\delta_9$	$\delta_{11}$	dummy	
1.9508	1.2924	5.8109	4.2796	4.1493	9.9246	11.0121	7.0165	6.8395	3.2029	7.4468	4.4889	8.7444	
1.8378	2.8823	2.8607	5.9252	3.2162	4.8053	1.2176	7.8602	4.8343	5.8595	4.4338	3.8853	3.6798	
3.4297	5.6365	4.3124	7.6887	3.7404	7.5913	2.8652	7.3114	6.9702	7.7754	7.4103	3.5533	7.0	

### TOP-DOWN COEFFICIENT OF CONCORDANCE - TDCC

N	BE - S <sub>i</sub>		
	TDCC		
	t=100	t=500	t=1000
65-129	0.4929	0.6663*	0.6935*
129-257	0.3113	0.7439*	0.604*
257-513	-0.2016	0.6505*	0.8056**
513-1025	-0.2433	0.4904	0.901**
1025-2049	0.7276*	0.4633	0.4820

\*\* : p<0.01, \* : p<0.05

N	MDC - S <sub>Ti</sub>		
	TDCC		
	T=100	t=500	t=1000
65-129	0.0125	0.5152	0.3109
129-257	0.51	0.7013*	0.7927**
257-513	0.2607	0.6167*	0.2398
513-1025	0.3597	0.5067	0.9307**
1025-2049	0.2708	0.5082	0.4424

\*\* : p<0.01, \* : p<0.05

N	BE - S <sub>Ti</sub>		
	TDCC		
	t=100	t=500	t=1000
65-129	0.6164*	0.3617	0.6643*
129-257	-0.0131	0.8041**	0.7313*
257-513	-0.0093	0.6737*	0.2315
513-1025	-0.1466	0.5101	0.8651**
1025-2049	0.689*	0.4608	0.5803

\*\* : p<0.01, \* : p<0.05

N	Th1 - S <sub>i</sub>		
	TDCC		
	t=100	t=500	t=1000
65-129	0.0711	0.6911*	0.8467**
129-257	0.1506	0.6715*	0.4657
257-513	0.9122**	0.9476**	0.2794
513-1025	0.1933	0.5342	0.7736
1025-2049	0.4904	0.8637**	0.5737

\*\* : p<0.01, \* : p<0.05

N	MDC - S <sub>i</sub>		
	TDCC		
	t=100	t=500	t=1000
65-129	0.5298	0.3936	0.5483
129-257	0.5937*	0.8543**	0.6643*
257-513	0.3296	0.7861**	0.6239*
513-1025	0.2045	0.6296*	0.3586
1025-2049	0.4476	0.6138*	0.6026*

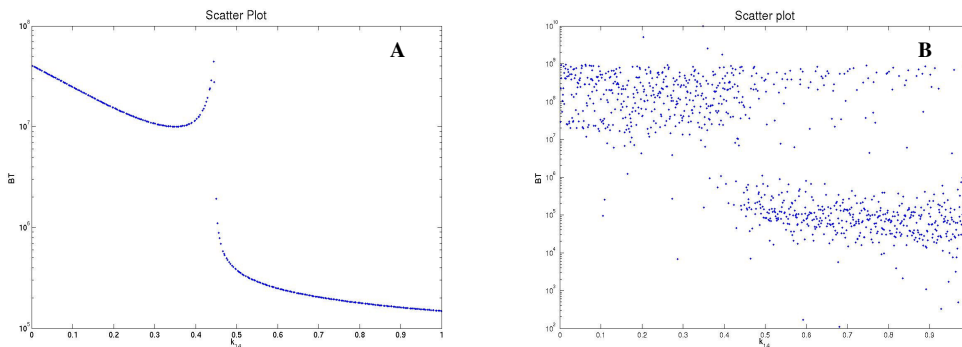
\*\* : p<0.01, \* : p<0.05

N	Th1 - S <sub>Ti</sub>		
	TDCC		
	t=100	t=500	t=1000
65-129	0.3856	0.0535	0.3989
129-257	0.679*	0.4672	-0.0208
257-513	0.0413	0.3495	0.1629
513-1025	0.2493	0.2959	0.4231
1025-2049	0.1544	0.6759*	0.6809*

\*\* : p<0.01, \* : p<0.05

## Supplement F: The effect of different parameter ranges on US analysis results

The choice of parameter ranges can affect US analysis results. Here we show two examples: the first one is based on the 2 compartmental ODE model of section 4.3. Figure F.1 shows scatter plots (Panel A and B) of the output BT (total bacterial load) versus LHS sampled values of parameter  $k_{14}$  (sampled uniformly between 0.001 and 1). Parameter  $k_{14}$  is varied simultaneously with all the other parameters in Panel B while it is the only one varied in Panel A (the rest of the parameters are set to baseline levels from Table A.1). Panel A shows a nonlinear non-monotonic relationship that is less evident in Panel B. In fact, a significantly strong negative correlation exists between parameter  $k_{14}$  and total bacterial load (PRCC=-0.77,  $p < 1e-100$ ). If we zoom into the region where  $k_{14}$  is non-monotonic (between 0.2 and 0.44, see Panel A), the strong correlation previously observed is almost lost, although still significant (PRCC=-0.15,  $p < 1e-7$ ). Unless the choice of very small ranges for certain parameters is guided by some *a priori* knowledge, the sampling should be performed within the whole set of known and plausible values.



**Figure F.1:** How different LHS ranges can affect PRCC results for the two-compartmental model described in Section 4.3 of the main text and in Supplement E. Scatter plots and PRCC plots of  $k_{14}$  values (x-axis) versus total bacterial load (BT) levels (y-axis) at day 1000. Scatter plots are of raw data in a linear-log scale. The number of runs is equal to 1000, except for Panel A (300 runs). *Panel A:* Scatter plot of the raw data. Only  $k_{14}$  is varied (between  $10^{-3}$  and 1). *Panel B:* Scatter plot of the raw data. All parameters from Table A.1 are varied.  $k_{14}$  is varied between  $10^{-3}$  and 1.

The second example highlights how a completely different range of variation for some parameter can lead to completely different PRCC results. We use the HIV model described in section 4.2, and compare two sets of ranges for  $s$  and  $k_I$ : Set 2 has  $s$  varying in  $[1e^{-4}, 1]$  and  $k_I$  in  $[1e^{-4}, 1e^{-2}]$ , Set 1 has  $s$  varying in  $[1e^{-2}, 50]$  and  $k_I$  varying in  $[1e^{-7}, 1e^{-3}]$  (set 1 is the more biologically plausible according to (Perelson *et al.*, 1993) and it is the one used in section 4.2). The results are shown in Table F.1. Panels A and B show PRCC results for Set 1 and Set 2, respectively. Extended FAST results are shown in Panels C and D for Set 1 and Panels E and F for Set 2.

LHS/PRCC analysis shows how switching from Set 1 to Set 2, parameters  $\mu_T$  loses its significance while parameter  $r$  gains it. Parameters  $N_V$ ,  $\mu_V$ , and  $k_2$  have consistently significant PRCCs for both sets, while  $k_I$ , although still significant, has now a negative PRCC to viral load (-0.1696).

eFAST results seem less affected by changes in parameter ranges. In fact, Panels C and E return the same set of significant  $S_i$  as well as Panels D and F for  $S_{Ti}$ .  $S_{Ti}$  for parameter  $r$  and  $k_I$  in Panel D are only marginally significant ( $p < 0.05$ ): their values are much higher than the dummy but due to large coefficients of variations (greater than 15%, data not shown), any inference is not reliable. Although a larger  $N_S$  is needed to improve accuracy, eFAST results are relatively consistent between the two sets.

**Table F.1:** PRCC and eFAST results on the HIV model for two different set of ranges for the parameters: Set 1 and Set 2 (Set 2 is the more biologically plausible one). Free virus V is always the output and the time points tested are 2000 and 4000 hours. *Panel A:* PRCC for set 1 (NS=300). *Panel B:* PRCC for Set 2 (NS=300). *Panel C:* First order sensitivity index  $S_i$  for Set 1 ( $N_S=257$ ,  $N_R=5$ ). *Panel D:* Total order sensitivity index  $S_{Ti}$  for Set 1 ( $N_S=129$ ,  $N_R=5$ ). *Panel E:* First order sensitivity index  $S_i$  for Set 2 ( $N_S=2049$ ,  $N_R=5$ ). *Panel F:* Total order sensitivity index  $S_{Ti}$  for Set 2 ( $N_S=257$ ,  $N_R=5$ ) [( $*$ ): significant; i.e.,  $p<0.01$ ].

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0778	-0.3282*	0.0297	0.3815*	0.6702*	-0.0177	0.6763*	-0.6464*	0.0101
4000	0.0692	-0.3248*	0.0322	0.3865*	0.6739*	-0.0042	0.6824*	-0.6474*	0.0148

**Panel A: PRCC on Set 1.**

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0265	-0.0744	0.4616*	-0.1696*	0.7045*	-0.1121	0.6880*	-0.6591*	-0.0056
4000	0.0315	-0.0576	0.4666*	-0.1704*	0.6993*	-0.0997	0.6929*	-0.6579*	-0.0098

**Panel B: PRCC on Set 2**

<i>s</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.0073	0.0221	0.0348*	0.0445*	0.0830*	0.0033	0.0963*	0.1875*	0.0099
4000	0.0073	0.0221	0.0321*	0.0448*	0.0837*	0.0035	0.0940*	0.1884*	0.0103

**Panel C:  $S_i$  on Set 1.**

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N_V$	$\mu_V$	<i>dummy</i>
2000	0.4274	0.4781	0.5301*	0.6611*	0.5965*	0.4913	0.6274*	0.7491*	0.4180
4000	0.4209	0.4761	0.5090*	0.6603*	0.5984*	0.4979	0.6149*	0.7503*	0.4200

**Panel D:  $S_{Ti}$  on Set 1.**

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N$	$\mu_V$	<i>dummy</i>
2000	0.0150	0.0142	0.0284*	0.0242*	0.0753*	0.0229*	0.0776*	0.3232*	0.0184
4000	0.0150	0.0142	0.0284*	0.0240*	0.0753*	0.0229*	0.0776*	0.3232*	0.0184

**Panel E:  $S_i$ , Set 2.**

<i>time</i>	<i>s</i>	$\mu_T$	<i>r</i>	$k_1$	$k_2$	$\mu_b$	$N$	$\mu_V$	<i>dummy</i>
2000	0.3969	0.3747	0.4872	0.4493	0.5579*	0.4569	0.5734*	0.8480*	0.4222
4000	0.3969	0.3747	0.4872	0.4482	0.5579*	0.4569	0.5736*	0.8480*	0.4224

**Panel F:  $S_{Ti}$ , Set 2.**

## Supplement G: Delay Differential Equation model of immune response

**Table G.1**

**Table G.1:** initial conditions (cells or bacteria per  $\text{cm}^3$  of tissue), parameter definitions and values for the DDE model

<b>Initial Conditions</b>		
<i>Variable</i>	<i>Description</i>	<i>Value</i>
$X_U(0) = X_U^{\text{baseline}}$	Initial condition for uninfected cells	$1e^4$
$X_I(0) = X_I^{\text{baseline}}$	Initial condition for infected cells	0
$B(0) = B_0$	Initial condition for bacteria	20
$I_R(0) = I_R^{\text{baseline}}$	Initial condition for innate response	$1e^3$
$A_R(0) = A_R^{\text{baseline}}$	Initial condition for adaptive response	$1e^2$

<b>Parameters</b>		
<i>Parameter</i>	<i>Description</i>	<i>Range</i>
$\mu_{X_U}$	Half-life of $X_U$ (like macrophages)	0.011
$\alpha_1$	Rate of infection	$[1e^{-4} - 1e^{-2}]$
$\alpha_2$	Rate of killing of $X_I$ due to $A_R$	$[1e^{-4} - 1e^{-2}]$
$\mu_{X_I}$	Half-life of $X_I$	0.011
$\alpha_{20}$	Growth rate of B	$[1e^{-1} - 1]$
$\sigma$	Max # of bacteria (threshold)	$[1e^3 - 1e^6]$
$\alpha_3$	Rate of killing of B due to $I_R$	$[1e^{-5} - 1e^{-3}]$
$\alpha_4$	Rate of killing of B due to $A_R$	$[1e^{-6} - 1e^{-3}]$
$\mu_{I_R}$	Half-life of innate immunity cells (10-fold higher than $\mu_{X_U}$ )	0.11
$\mu_{A_R}$	Half-life of adaptive immunity cells (T Helper cells)	0.3333
$\tau_1$	Delay of innate immunity	$[1e^{-2}, 10]$
$\tau_2$	Delay of adaptive immunity	$[1e^{-1}, 40]$



**Table G.2:** PRCC and eFAST results of the delay differential equation model (20)-(24) at five different time points [10 30 50 100 200]. [(\*): significant; i.e.,  $p < 0.01$ ]. The output chosen for SA is bacterial load. Sample size for LHS/PRCC is  $N=1000$ . For eFAST,  $N_S=65$  and  $N_R=20$ . *Panel A:* PRCC calculated using the entire LHS matrix. *Panel B:* PRCC calculated using the subset of the LHS matrix not satisfying condition (25) (see main text, section 4.4). *Panel C:* PRCC calculated using the subset of the LHS matrix satisfying condition (25) (see main text, section 4.4). *Panel D:* First-order eFAST sensitivity indexes. *Panel E:* Total-order eFAST sensitivity indexes.

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	-0.0196	-0.0523	0.0623	-0.0001	-0.9808*	-0.5072*	0.9716*	0.0176	-0.0078
30	-0.2331*	-0.1034	0.0489	0.0182	-0.6153*	-0.1238	0.4335*	0.0634	-0.0393
50	-0.2226*	-0.1753*	0.0677	0.0324	-0.7730*	-0.1881*	0.6737*	0.0396	-0.0440
100	-0.1680*	-0.1268	0.0711	0.0279	-0.8247*	-0.2030*	0.7436*	0.0802	-0.0574
200	-0.1844*	-0.0904	0.0499	0.0006	-0.8195*	-0.1767*	0.7311*	0.0672	-0.0517

**Panel A:** PRCC on the entire LHS matrix

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	-0.0302	0.0027	0.0454	-0.0787	-0.8506*	-0.2965*	0.8117*	0.0197	-0.0254
30	-0.0314	-0.0266	0.0435	-0.0808	-0.8485*	-0.2856*	0.8137*	0.0161	-0.0284
50	-0.0149	-0.0173	0.0445	-0.0775	-0.8456*	-0.2678*	0.8166*	0.0188	-0.0238
100	0.0037	-0.0027	0.0431	-0.0766	-0.8436*	-0.2503*	0.8199*	0.0181	-0.0272
200	0.0089	0.0078	0.0431	-0.0779	-0.8434*	-0.2398*	0.8215*	0.0167	-0.0269

**Panel B:** PRCC on the LHS subset not satisfying condition (25)

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0066	-0.0490	0.0467	-0.0115	-0.8899*	-0.4329*	0.8691*	-0.0316	-0.0019
30	-0.4205*	-0.2811*	0.0494	0.0202	0.1144*	-0.1105	-0.3152*	0.0340	0.0452
50	-0.3615*	-0.3283*	0.1024	0.0187	-0.3008*	-0.1972*	0.1823*	-0.0310	0.0673
100	-0.2627*	-0.2577*	0.0853	0.0214	-0.3096*	-0.2099*	0.1898*	0.0454	0.0420
200	-0.2877*	-0.2288*	0.0628	0.0013	-0.2815*	-0.1650*	0.1283*	0.0197	0.0239

**Panel C:** PRCC on the LHS subset satisfying condition (25)

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0279*	0.0484*	0.0228	0.0112	0.2877*	0.0583*	0.1523*	0.0221	0.0165
30	0.0733*	0.1157*	0.0600	0.0484	0.2045*	0.0850	0.1004*	0.0519	0.0376
50	0.1173*	0.0983*	0.1202	0.0978	0.1478*	0.0818*	0.1366*	0.0668	0.0792
100	0.1134*	0.0992	0.0967	0.1139	0.1904*	0.0974	0.1274*	0.1178	0.0895
200	0.1227	0.1234	0.1131	0.1042	0.1613*	0.0872	0.1142*	0.0892	0.0916

**Panel D:** first-order sensitivity index  $S_i$

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.2103*	0.3826*	0.2089	0.1150	0.8409*	0.3955*	0.6485*	0.2033	0.1678
30	0.5437*	0.6839*	0.4734	0.3980	0.8727*	0.6393	0.7365*	0.4178	0.3191
50	0.8218*	0.6931*	0.8050	0.7129	0.8694*	0.5811*	0.7133*	0.5210	0.5895
100	0.8037*	0.7628	0.7179	0.7033	0.8817*	0.6675*	0.7451*	0.8272	0.6959
200	0.7817	0.8584	0.7783	0.7824	0.8863*	0.6620	0.7181*	0.7004	0.6568

**Panel E:** total-order sensitivity index  $S_{Ti}$

**Table G.3: detailed eFAST results on the delay model in section 4.4 of the manuscript.**

**S<sub>i</sub>, NS=65, NR=5**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0193	0.0155	0.0132	0.0079	0.1984*	0.0414	0.1723*	0.0220	0.0090
30	0.0443	0.1458	0.0533	0.0270	0.2866*	0.1000*	0.1146	0.0515	0.0372
50	0.1008	0.1487	0.0977	0.0456	0.1586*	0.0886*	0.1133*	0.0880	0.0182
100	0.0966	0.1100	0.0779	0.0993	0.1315*	0.1345	0.1299*	0.1201	0.0658
200	0.0852	0.0958	0.0992	0.0992	0.2730*	0.1018	0.1113	0.1053	0.0926

**CV<sub>s<sub>i</sub></sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	144.2654	125.2001	95.1143	111.8739	68.8894	58.1539	96.5936	143.9488	152.0000
30	53.2870	149.5556	122.5190	124.0243	100.5846	104.8757	127.1269	142.8619	83.9657
50	168.5867	141.1228	152.0239	103.8887	81.2937	102.2800	87.9667	156.6263	58.1359
100	133.8536	111.3795	102.2914	192.1373	76.9156	111.3086	97.1914	139.8560	126.5793
200	154.6319	135.1095	143.2305	141.8523	90.3385	96.2441	96.8879	99.0502	138.2250

**S<sub>Ti</sub>, NS=65, NR=5**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.1553	0.1447	0.1246	0.0880	0.8630*	0.3267	0.6261*	0.1849	0.0833
30	0.3413	0.8676	0.4198	0.2481	0.8840*	0.6482*	0.7960*	0.4128	0.2873
50	0.7265	0.7656	0.7471	0.3695	0.8453*	0.6560*	0.7613*	0.6410	0.1835
100	0.7230	0.8396	0.5391	0.7290	0.8704*	0.8044	0.8068*	0.8238	0.5120
200	0.7551	0.7569	0.5721	0.7509	0.7872*	0.7006	0.7293	0.7494	0.8023

**CV<sub>S<sub>Ti</sub></sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	168.9324	131.5928	97.1150	114.7382	108.0382	128.5753	100.0953	134.1547	142.8055
30	82.2733	139.3402	128.1334	106.8218	100.0881	136.5247	104.9496	124.9635	86.8417
50	178.4657	130.9297	151.3264	108.3445	100.6122	112.9897	103.9011	149.7184	59.3725
100	136.3796	119.0967	98.7360	180.9233	101.4618	135.9653	104.9138	132.2905	125.8226
200	158.5934	123.7234	116.8643	138.8972	99.8849	111.0587	97.7849	113.2401	141.9040

**S<sub>i</sub>, NS=65, NR=20**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0279*	0.0484*	0.0228	0.0112	0.2877*	0.0583*	0.1523*	0.0221	0.0165
30	0.0733*	0.1157*	0.0600	0.0484	0.2045*	0.0850	0.1004*	0.0519	0.0376
50	0.1173*	0.0983*	0.1202	0.0978	0.1478*	0.0818*	0.1366*	0.0668	0.0792
100	0.1134*	0.0992	0.0967	0.1139	0.1904*	0.0974	0.1274*	0.1178	0.0895
200	0.1227	0.1234	0.1131	0.1042	0.1613*	0.0872	0.1142*	0.0892	0.0916

**CV<sub>s<sub>i</sub></sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	123.5034	194.8934	186.1062	138.6807	85.2739	83.7584	86.4593	214.2552	176.1004
30	72.2393	118.3395	138.5375	124.2849	79.0369	147.3545	130.4251	120.1901	96.3386
50	123.1391	133.4148	220.6788	217.9033	62.3055	104.8393	107.6511	135.6042	188.8654
100	131.0480	134.6358	170.6628	192.1874	77.5074	128.2992	97.0451	253.5032	156.1838
200	141.8747	142.2387	152.2826	168.8486	62.1730	103.0352	90.0777	168.6053	124.5279

**S<sub>Ti</sub>, NS=65, NR=20**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.2103*	0.3826*	0.2089	0.1150	0.8409*	0.3955*	0.6485*	0.2033	0.1678
30	0.5437*	0.6839*	0.4734	0.3980	0.8727*	0.6393	0.7365*	0.4178	0.3191
50	0.8218*	0.6931*	0.8050	0.7129	0.8694*	0.5811*	0.7133*	0.5210	0.5895
100	0.8037*	0.7628	0.7179	0.7033	0.8817*	0.6675*	0.7451*	0.8272	0.6959
200	0.7817	0.8584	0.7783	0.7824	0.8863*	0.6620	0.7181*	0.7004	0.6568

**CV<sub>S<sub>Ti</sub></sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	137.9708	207.2900	180.5670	141.3824	101.9384	138.9739	102.3148	192.9522	179.9271
30	113.1428	125.2775	139.8100	126.1887	99.9394	152.2993	112.9639	122.7075	102.6616
50	132.7011	131.7841	205.7701	203.9145	104.7785	117.8112	107.0298	138.9706	185.9341
100	135.1186	133.9035	166.2474	164.3342	99.8418	132.3673	106.5909	220.3176	150.8193
200	130.5880	142.0687	149.9027	164.9461	100.8980	116.6368	99.1134	166.0701	131.6336

**S<sub>i</sub>, NS=129, NR=5**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0041	0.0098	0.0023	0.0014	0.3218*	0.0275	0.1038*	0.0028	0.0122
30	0.0593	0.0975	0.0169	0.0215	0.1980*	0.0493	0.0532*	0.0278	0.0062
50	0.0544	0.0438	0.0412	0.0310	0.1997*	0.0345	0.0566	0.0174	0.0393
100	0.0410	0.0546	0.0287	0.0426	0.1340*	0.0505	0.0589	0.0415	0.0383
200	0.0497	0.0424	0.0516	0.0221	0.2126*	0.0544*	0.0806*	0.0638	0.0231

**CV<sub>S<sub>i</sub></sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	71.2365	145.8554	173.0452	123.9713	91.4324	35.9810	83.8815	114.1534	346.8012
30	187.7353	158.6901	206.8257	157.5746	89.0176	124.9555	102.9165	258.8308	121.4591
50	178.5905	116.1862	212.6679	153.0807	99.2300	73.4102	133.4740	75.3306	186.2718
100	122.7088	106.2554	111.3175	130.5122	65.7280	100.4312	112.5976	115.4544	158.9387
200	192.1068	114.7978	135.3213	77.1318	89.2582	88.3393	106.7728	151.2681	125.4024

**S<sub>Ti</sub>, NS=129, NR=5**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0798	0.1196	0.0545	0.0814	0.8446*	0.2605	0.6402*	0.0588	0.2164
30	0.6579	0.8326*	0.3021	0.4127	0.8845*	0.6275	0.7922*	0.4227	0.1123
50	0.7329	0.6094	0.5589	0.4036	0.8440*	0.4904	0.6441	0.3892	0.6198
100	0.6001	0.7224	0.4829	0.7218	0.8868*	0.7709	0.6248*	0.6512	0.5546
200	0.7933	0.7079	0.7207	0.4903	0.8559*	0.7350	0.8030*	0.7662	0.3532

**CV<sub>S<sub>Ti</sub></sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	128.5294	146.3572	162.5094	191.1825	102.0818	82.3899	99.8350	119.7284	280.6353
30	194.1368	138.5858	185.5372	157.9181	99.5853	134.8921	102.4297	204.8226	90.2079
50	185.5236	124.9957	177.0138	135.2357	100.6843	82.6950	97.2470	100.5041	165.2885
100	155.8439	121.0368	114.4024	147.5088	101.2867	112.7190	91.1713	121.1986	150.2241
200	207.1623	120.5593	138.2513	95.9509	101.5652	98.9193	107.9415	123.3462	114.7024

**S<sub>i</sub>, NS=257, NR=5**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0104*	0.0011	0.0003	0.0004	0.2301*	0.0212*	0.0977*	0.0001	0.0022
30	0.0136	0.0450	0.0029	0.0035	0.1642*	0.0228	0.0390	0.0017	0.0093
50	0.0280*	0.0257	0.0024	0.0287	0.0842*	0.0229	0.0581*	0.0022	0.0124
100	0.0373	0.0283	0.0162	0.0243	0.0857*	0.0324	0.0339	0.0135	0.0251
200	0.0161	0.0202	0.0224	0.0240	0.1471*	0.0303*	0.0300	0.0300	0.0174

**CV<sub>si</sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	86.3487	27.3484	80.5021	290.2131	87.5709	85.5194	85.0168	103.8637	213.0735
30	97.0851	127.0033	44.8454	59.2454	78.1014	130.0295	66.0919	228.9163	177.2243
50	84.9230	67.3211	40.1802	307.2208	72.7816	93.6995	90.7535	141.2189	100.6158
100	95.2407	108.7243	99.3350	147.7580	73.2456	108.0513	71.0819	113.1675	157.6277
200	88.0191	86.1555	114.4780	177.7660	89.3528	85.1934	72.8476	139.2297	103.5820

**S<sub>Ti</sub>, NS=257, NR=5**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	0.0855*	0.0666	0.0131	0.0294	0.8468*	0.2886*	0.6696*	0.0024	0.0947
30	0.2044	0.4146	0.1262	0.2335	0.8654*	0.4172	0.7630*	0.0979	0.3334
50	0.5472*	0.6230	0.1354	0.7427	0.8642*	0.5633	0.7016*	0.1274	0.5306
100	0.5350	0.7781	0.5180	0.5925	0.8790*	0.6554	0.8633	0.4570	0.7366
200	0.4122	0.6197	0.7607	0.7843	0.8654*	0.7980*	0.8649	0.6367	0.6476

**CV<sub>STi</sub>**

time	$\tau_1$	$\tau_2$	$\alpha_1$	$\alpha_2$	$\alpha_3$	$\alpha_4$	$\alpha_{20}$	$\sigma$	dummy
10	94.0727	116.4093	83.6897	266.7391	101.8729	111.8459	101.7834	106.6204	222.5645
30	131.7662	108.6579	58.6523	85.7069	99.2924	133.3653	98.8405	131.6591	164.3038
50	93.1519	104.9844	56.8415	245.1413	103.0454	97.9293	97.7897	130.0527	125.7261
100	96.3868	124.5996	126.7015	153.2688	102.0666	96.5287	104.1681	112.4437	148.2535
200	82.7744	104.1613	124.8783	163.8216	102.0238	104.6895	109.0801	124.7261	113.6821

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