

20th HIV Dynamics &
Evolution
May 8-11, 2013



Organizers: Drs. Rob De Boer, José Borghans, Monique Nijhuis and Can Keşmir

Attempting to quantify T cell turnover

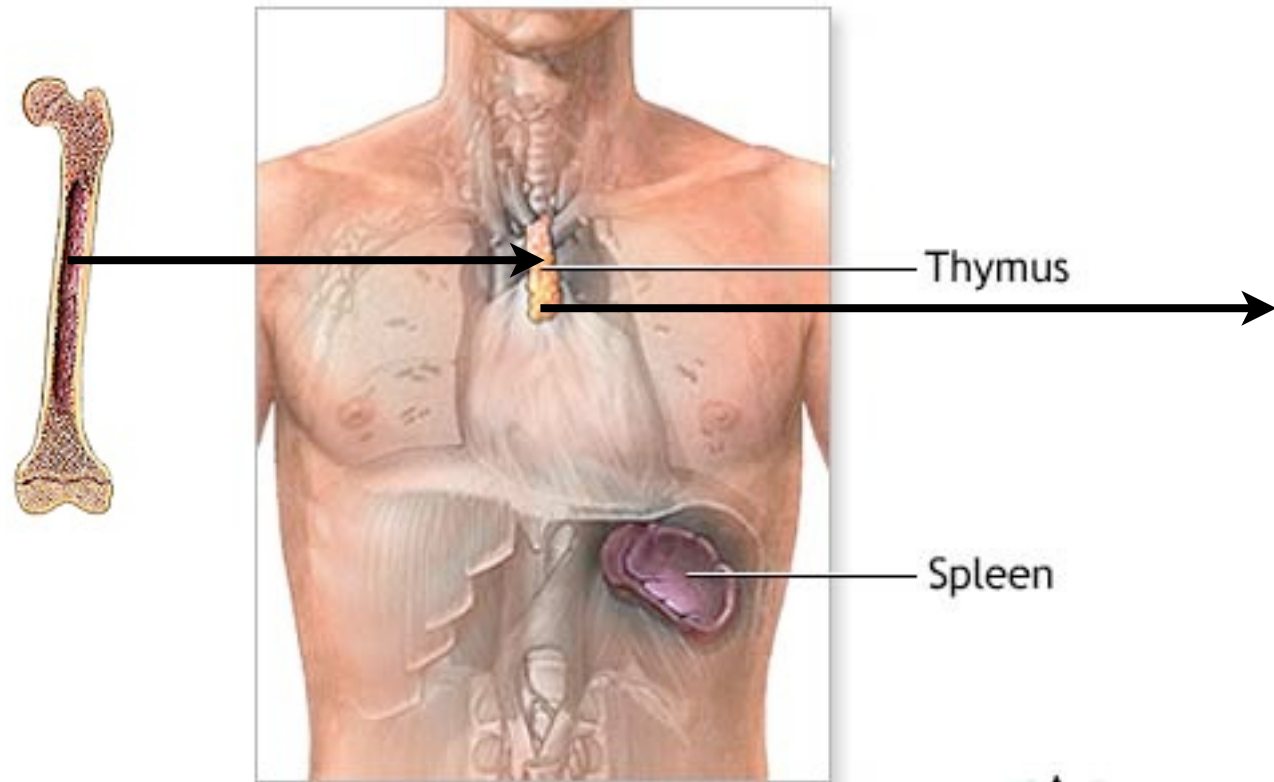
Long-lived memory is maintained
by short-lived cells

Rob J. De Boer

Theoretical Biology & Bioinformatics

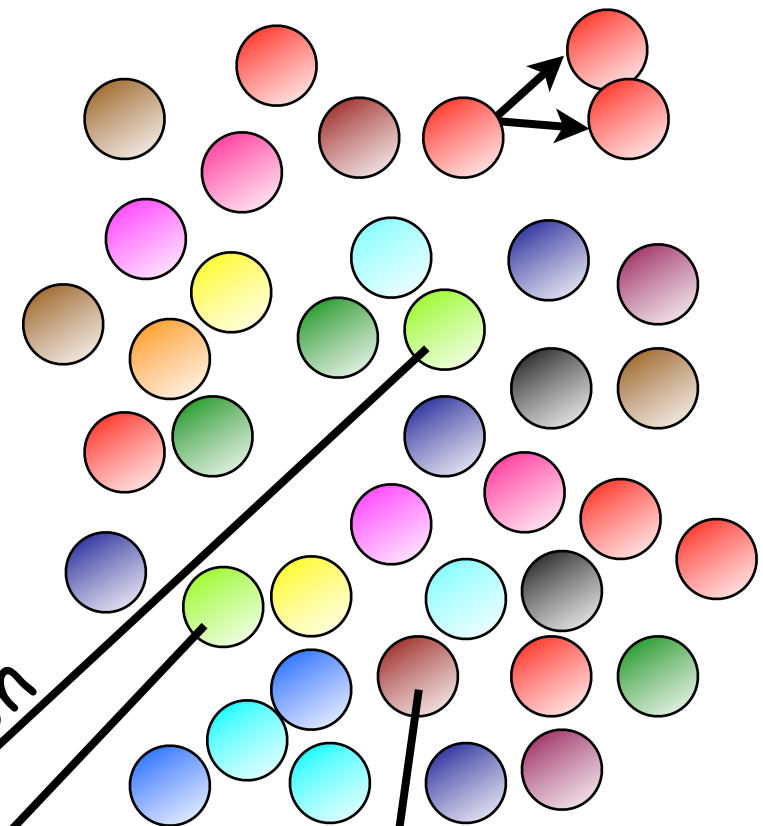
Utrecht University





ADAM.

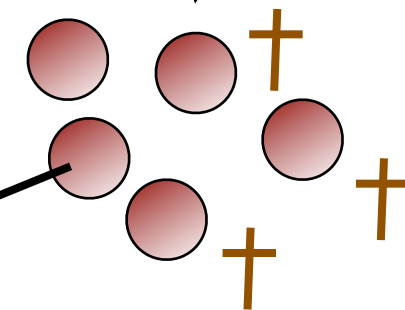
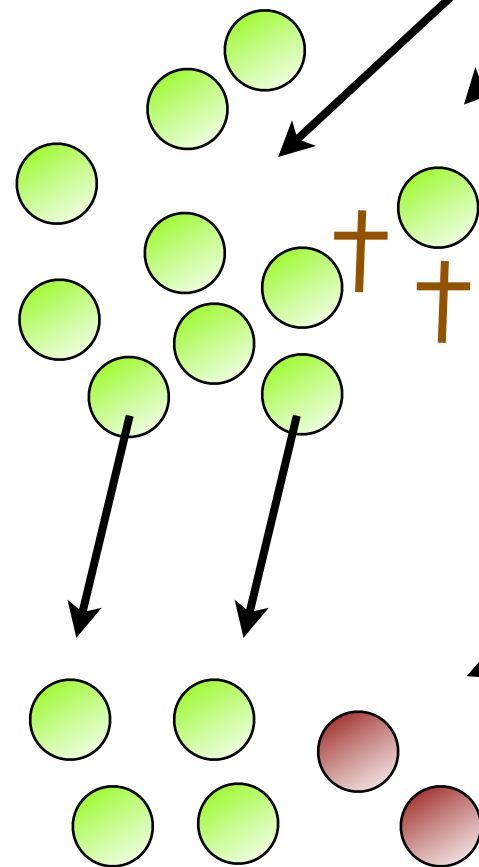
Naive T cells



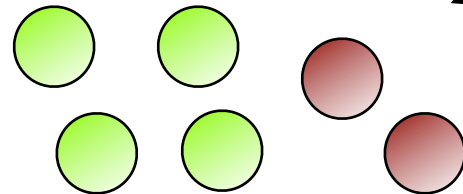
infection

clonal expansion

Activated cells
Effector cells

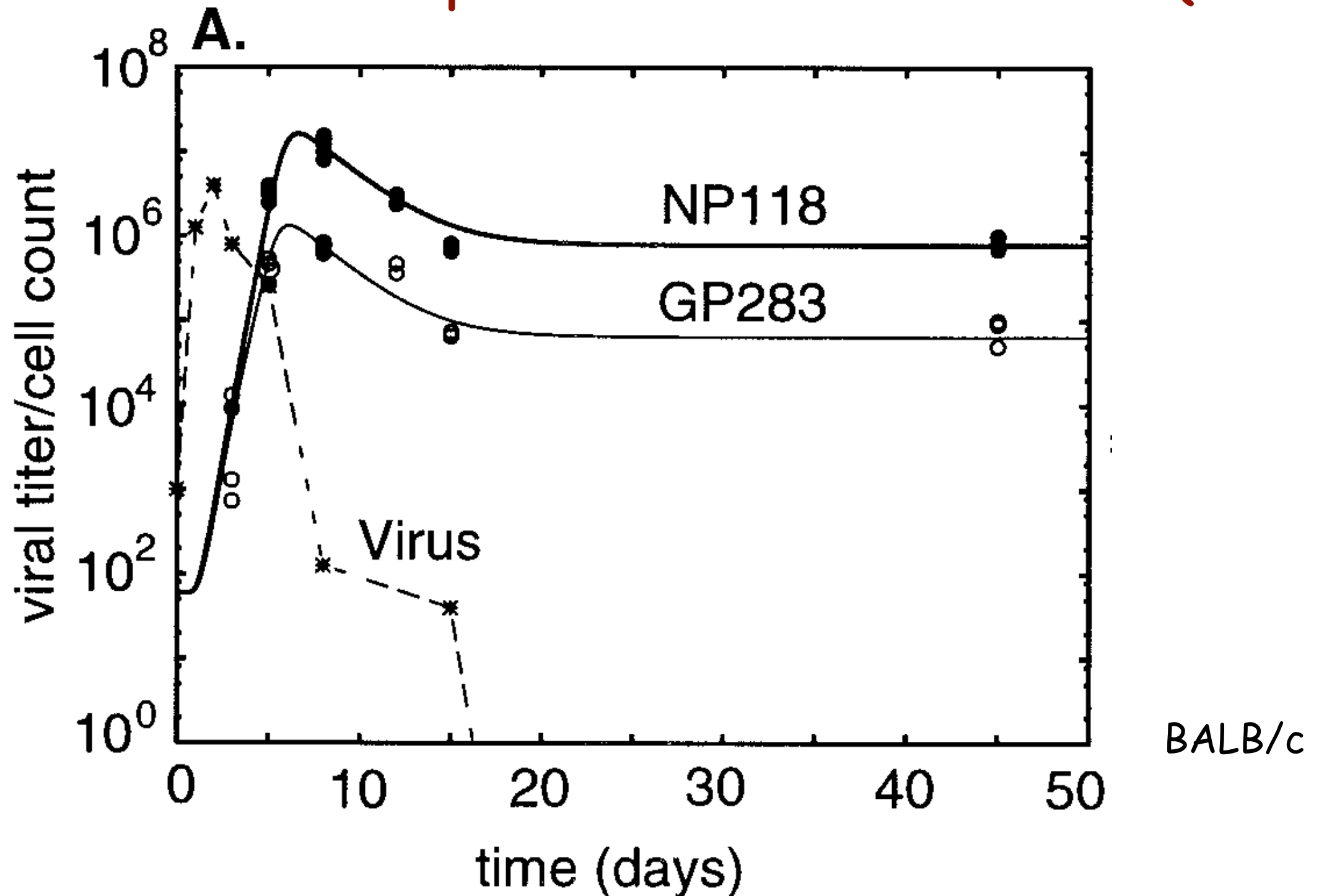


Memory T cells



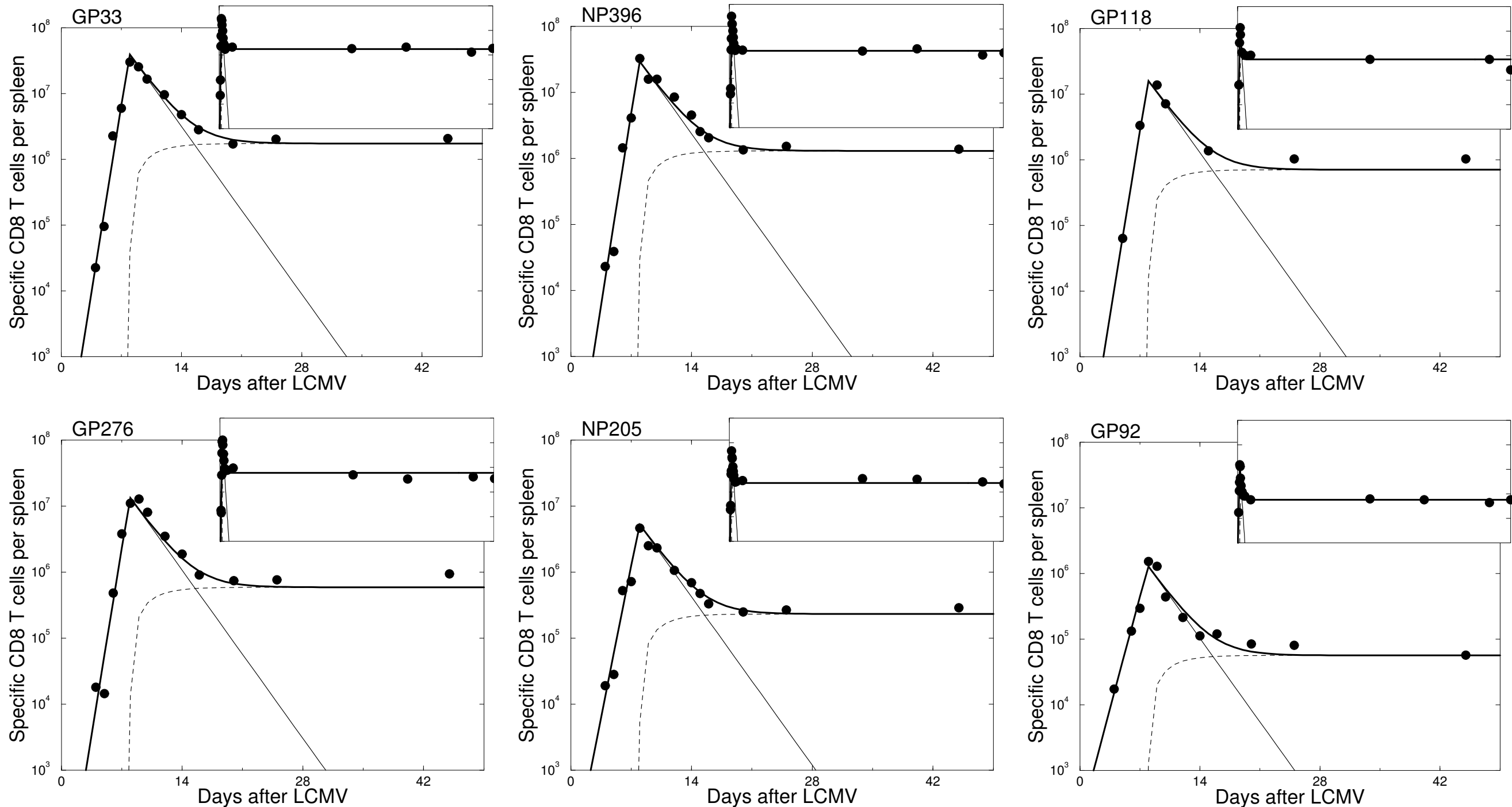
$$\frac{dT}{dt} = s + (p - d)T$$

A T cell immune response to a mouse virus (LCMV)



Just a few cells (< 100) start divide around day 3, they peak at day 8, decline, and then persist (memory)

CD8 T cell responses to several "epitopes" of the virus



Inset is 912 days: memory lasts "forever"

Towards a more quantitative immunology

Systems biology: new type of questions:

What is the expected life span of a normal naive T cell, and how are these cells maintained (thymus/renewal & mouse/man*)?

What is the life span of an effector/memory T cell?

How does a virus like HIV interfere with these normal population dynamics, and how does that cause the depletion of CD4⁺ T cells?

What fraction of the naive T cell population is composed of short-lived RTE and long-lived truly naive T cells, and what is actually the expected life span within each subset?

Approach:

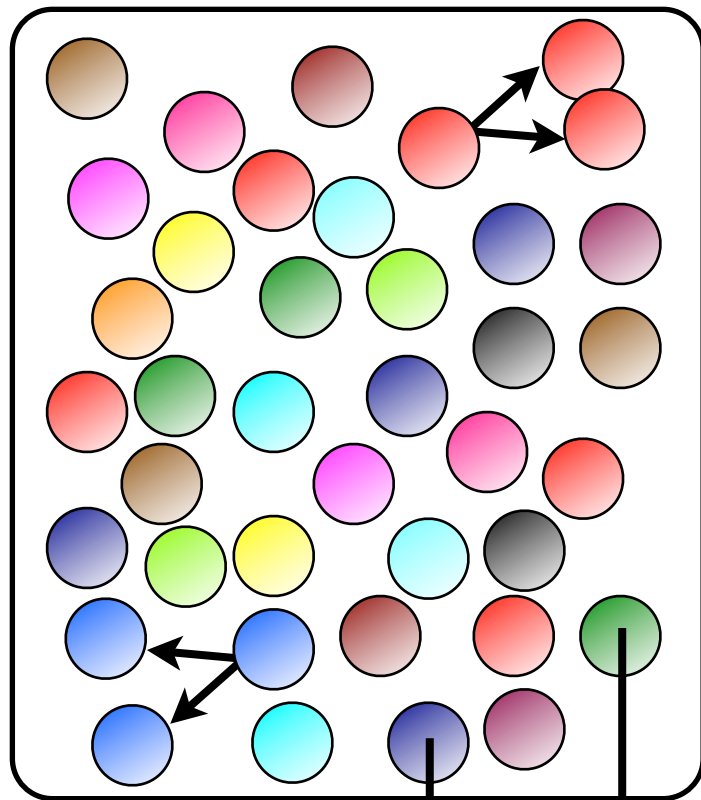
Labeling experiments with deuterium, BrdU and CFSE

Interpret data with **appropriate** mathematical models

* Den Braber et al. Immunity 2012

Population at steady state maintained by renewal

Memory T
cells

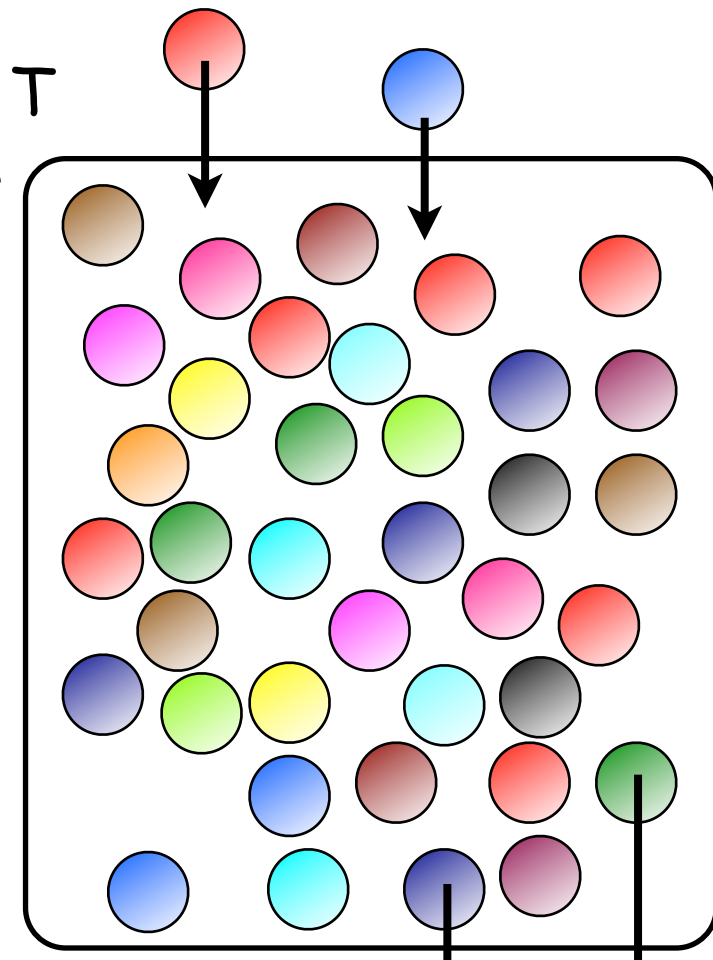


Turnover rate,
average life span, residence
time, interdivision time

$$\frac{dT}{dt} = s + (p - d)T = 0$$

source

Naive T
cells



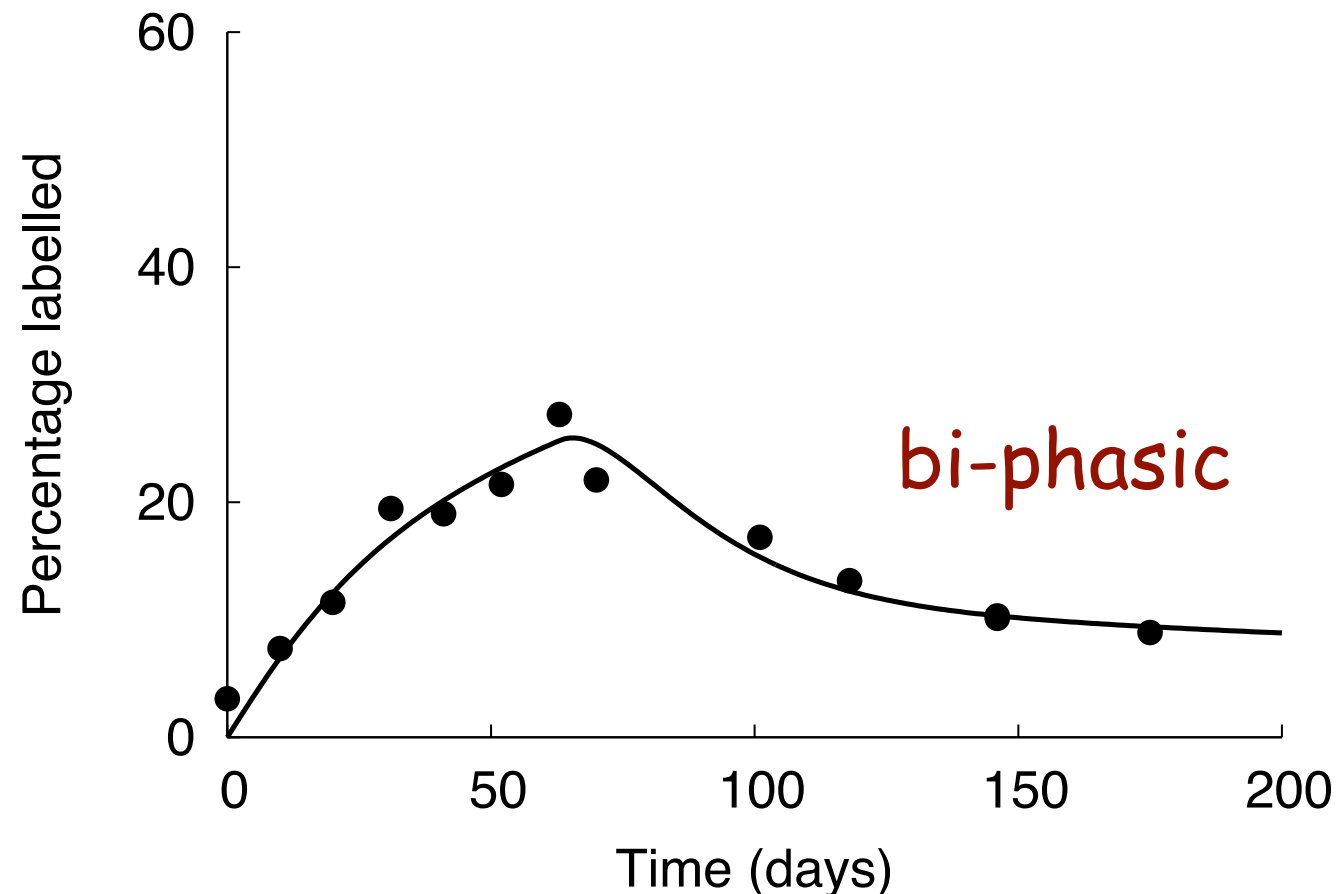
Turnover rate, average
life span, residence time

#new cells
=
#cells lost

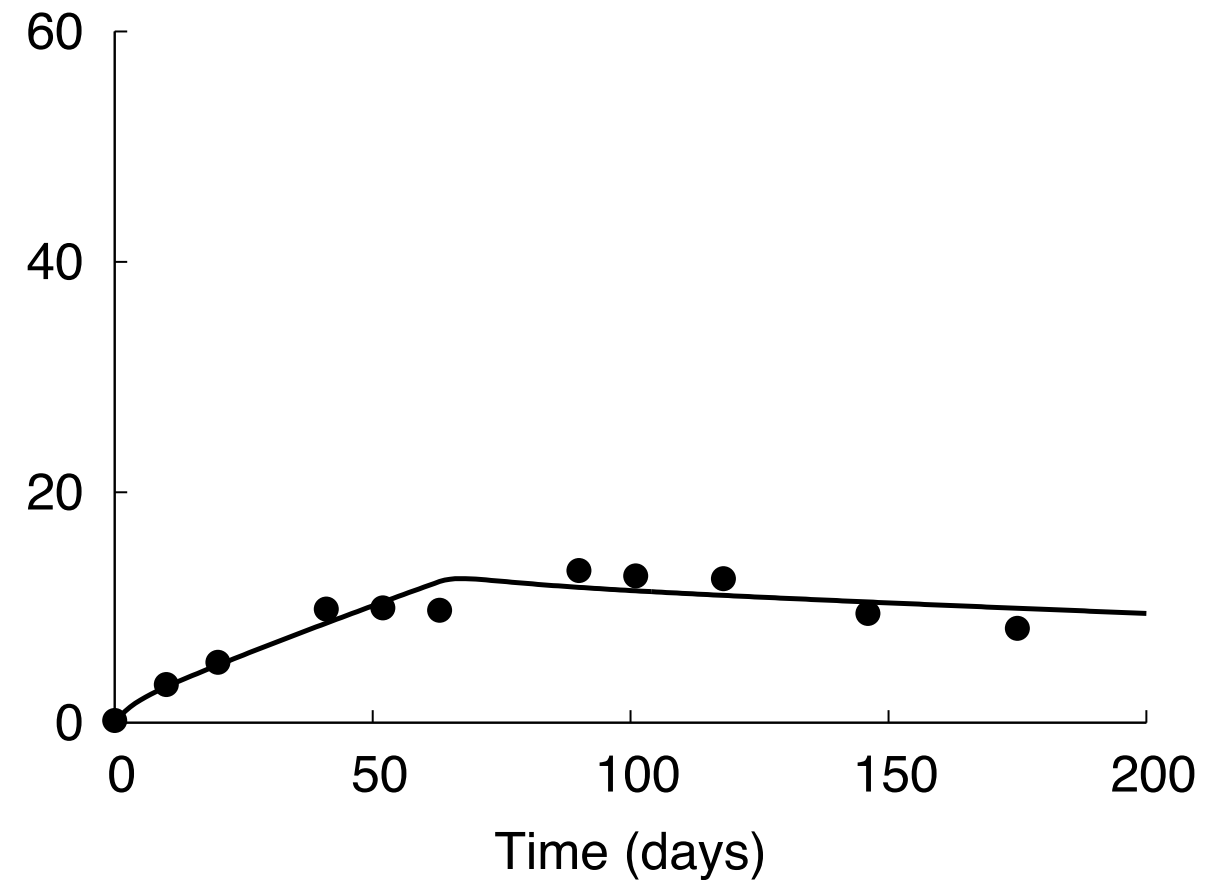
Examples of labeling with deuterium in volunteers

Memory T cells: CD45RO⁺

CD4 M (a) Healthy



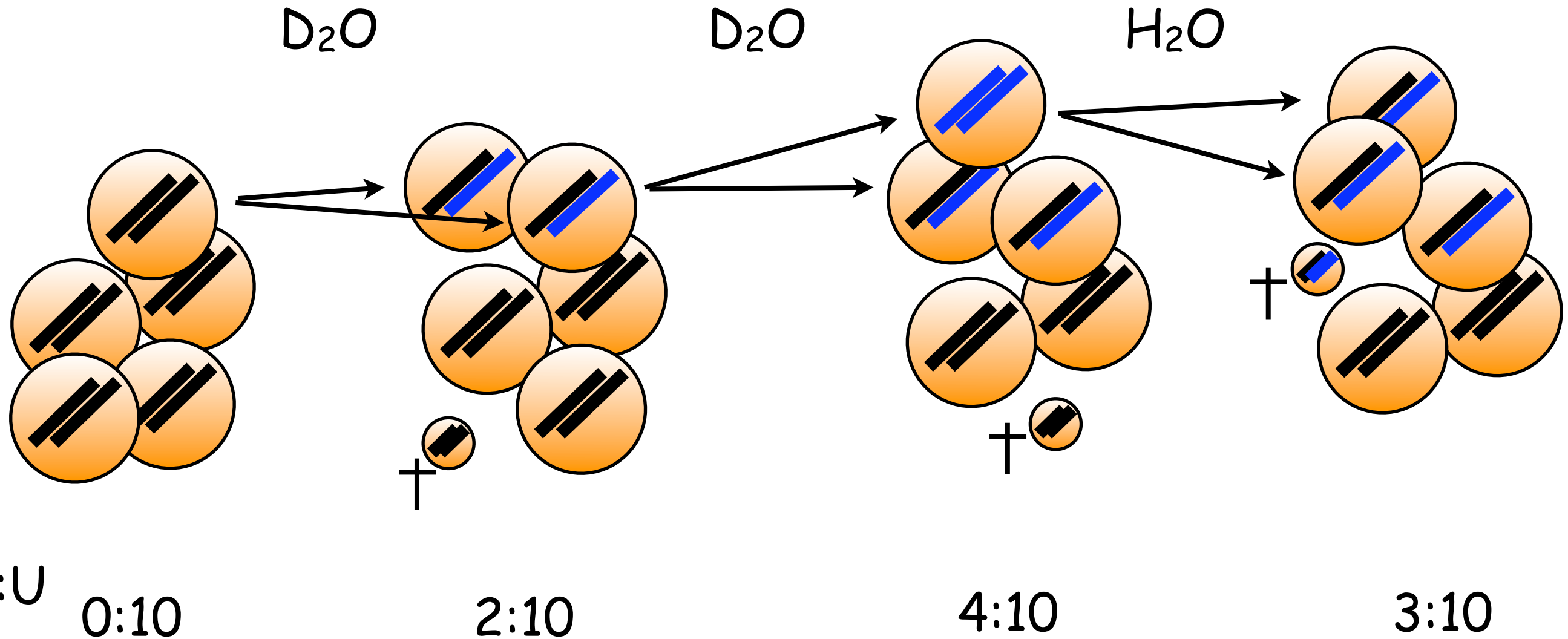
CD8 M (a) Healthy



People drink 4% heavy water for T=9 weeks and are followed for another 16 weeks. Naive and memory T cells are sorted from the blood and the deuterium enrichment in their DNA is measured by mass-spec

Deuterium labeling much easier to interpret than BrdU labeling

Modeling seems relatively easy



DNA strands largely disappear by cell death.

Model loss of unlabeled strands during up-labeling:

$$dU/dt = -dU \text{ or } L(t) = 1 - e^{-dt}$$

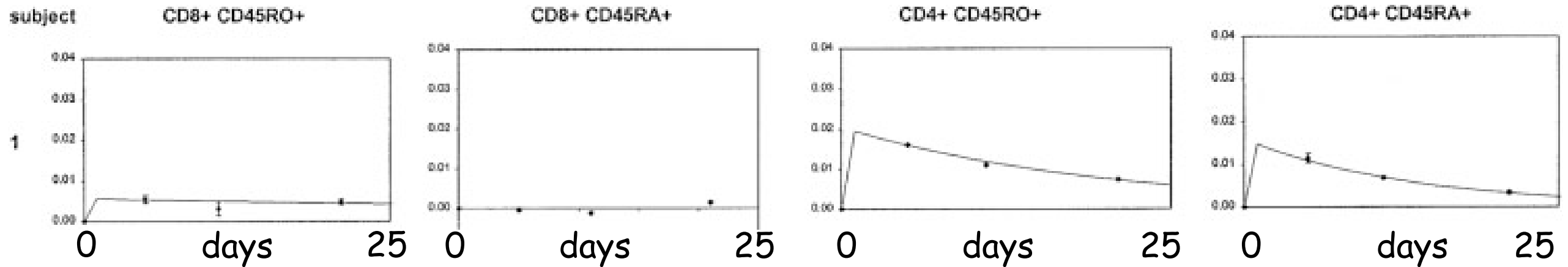
and the loss of labeled strands during down-labeling:

$$dL/dt = -dL \text{ or } L(t) = L(T)e^{-d(t-T)}$$

T: labeling period

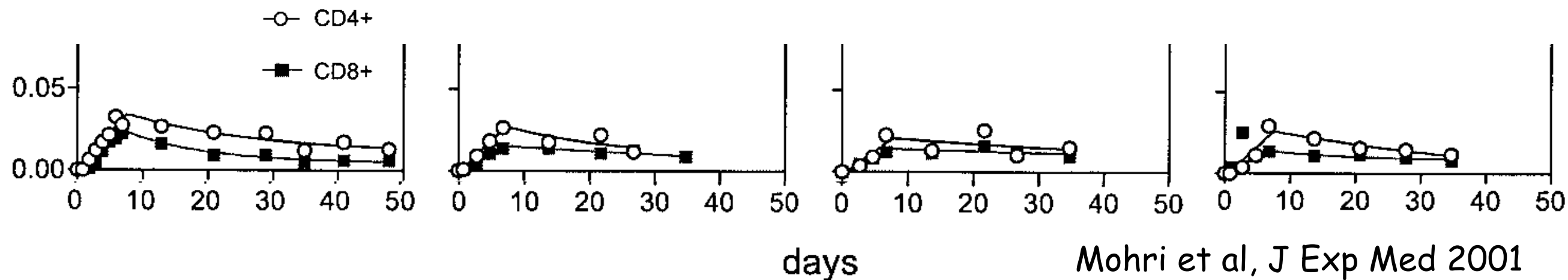
Three examples of quite different deuterium studies

Enrichment



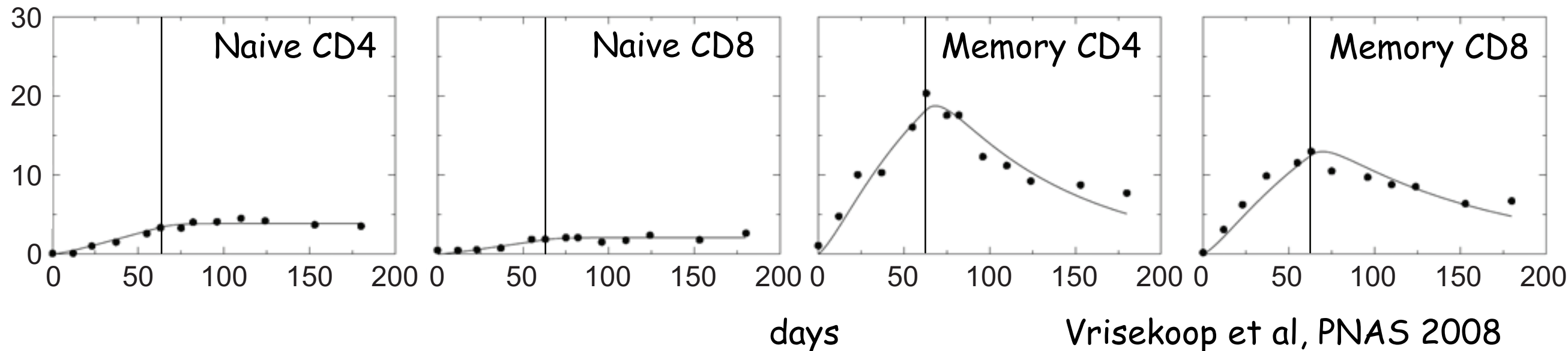
Macallan et al, Eur J Imm 2003

Enrichment



Mohri et al, J Exp Med 2001

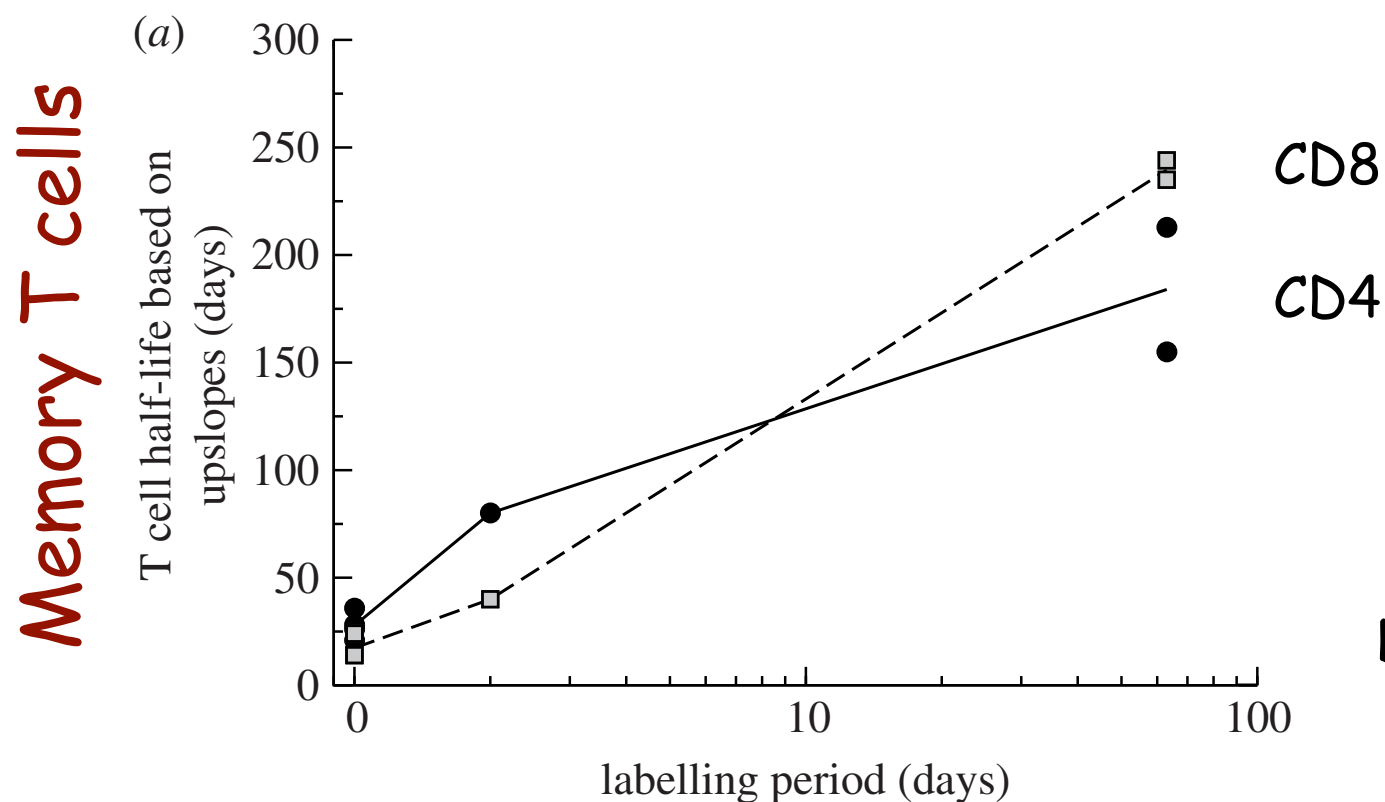
Enrichment (%)



Vrisekoop et al, PNAS 2008

Short studies D-glucose and long study D-water

Length of labeling period increases estimated life spans



De Boer et al, J Roy Soc Int 2012

Table 1. Average half-lives (in days) of different T-cell populations in healthy individuals estimated by stable isotope labeling

Reference	(2)	(53)	(54)	(7)	(8)	(55)	(56)	(57)	(Vrisekoop et al.)
Method	$^2\text{H}_2$ -glucose	$^2\text{H}_2$ -glucose	$^2\text{H}_2\text{O}$	$^2\text{H}_2$ -glucose	$^2\text{H}_2$ -glucose	$^2\text{H}_2$ -glucose	$^2\text{H}_2$ -glucose	$^2\text{H}_2$ -glucose	$^2\text{H}_2\text{O}$
Label period	2 days	2 days	9 weeks	1 week	1 week	1 day	1 day	1 day	9 weeks
Model	pp	pp	pp	1comp	2comp	Asq	Asq	Asq	Asq
CD4	87	82	385	173	154				
CD8	77	139	420	231	257				
Naive CD4		187				118	361	119	184
Naive CD8		204				154		131	112
Memory CD4		80	213			26	21	28	36
Memory CD8		40	235			14		18	24
									1517
									2398
									155
									244

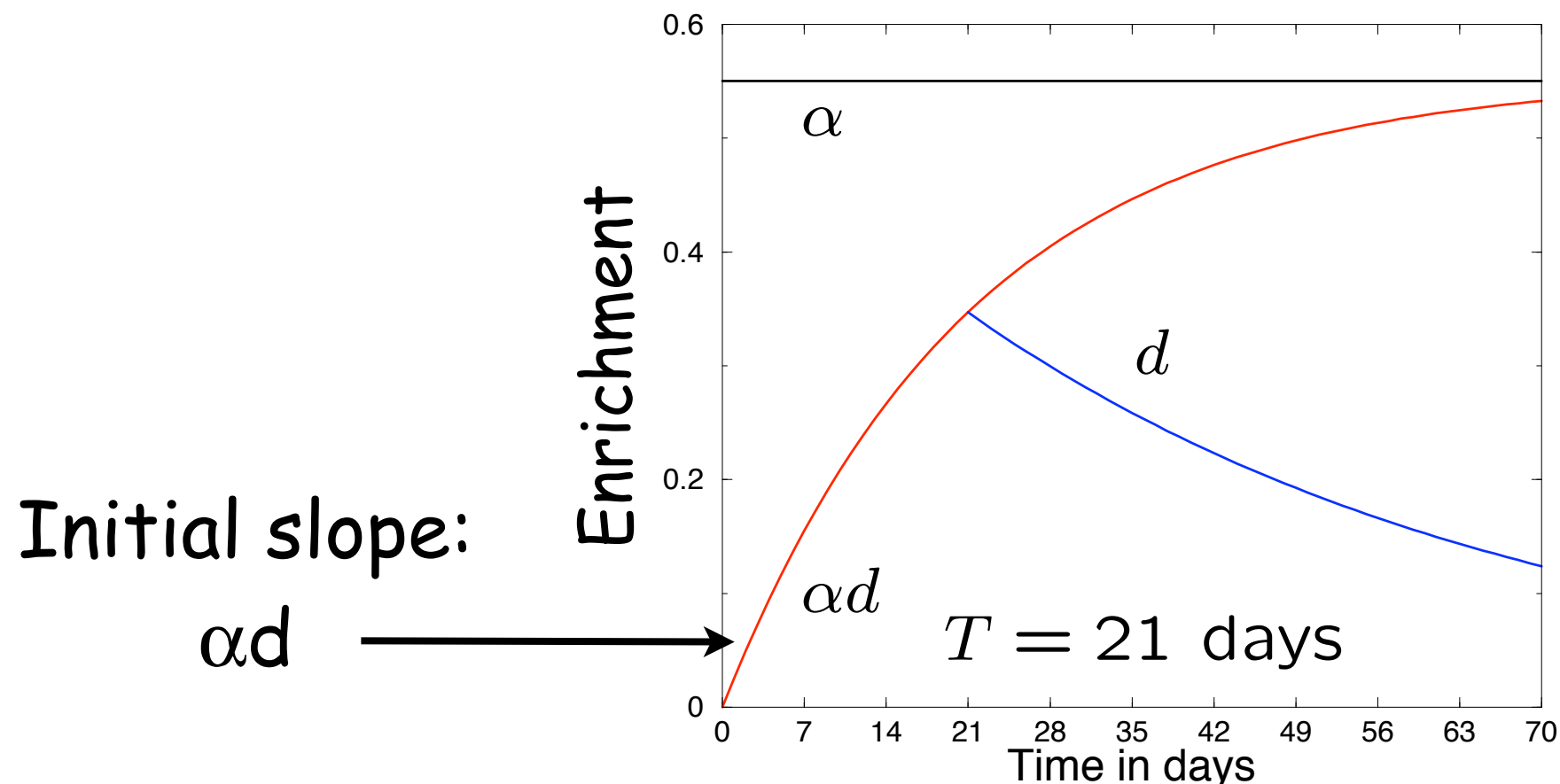
Data have mostly been interpreted with models having one exponential

$$L(t) = \begin{cases} \alpha(1 - e^{-dt}) , & \text{if } t \leq T_{\text{end}} , \\ L(T_{\text{end}})e^{-d(t-T_{\text{end}})} , & \text{otherwise ,} \end{cases}$$

with asymptote α , turnover rate d & average turnover rate αd .

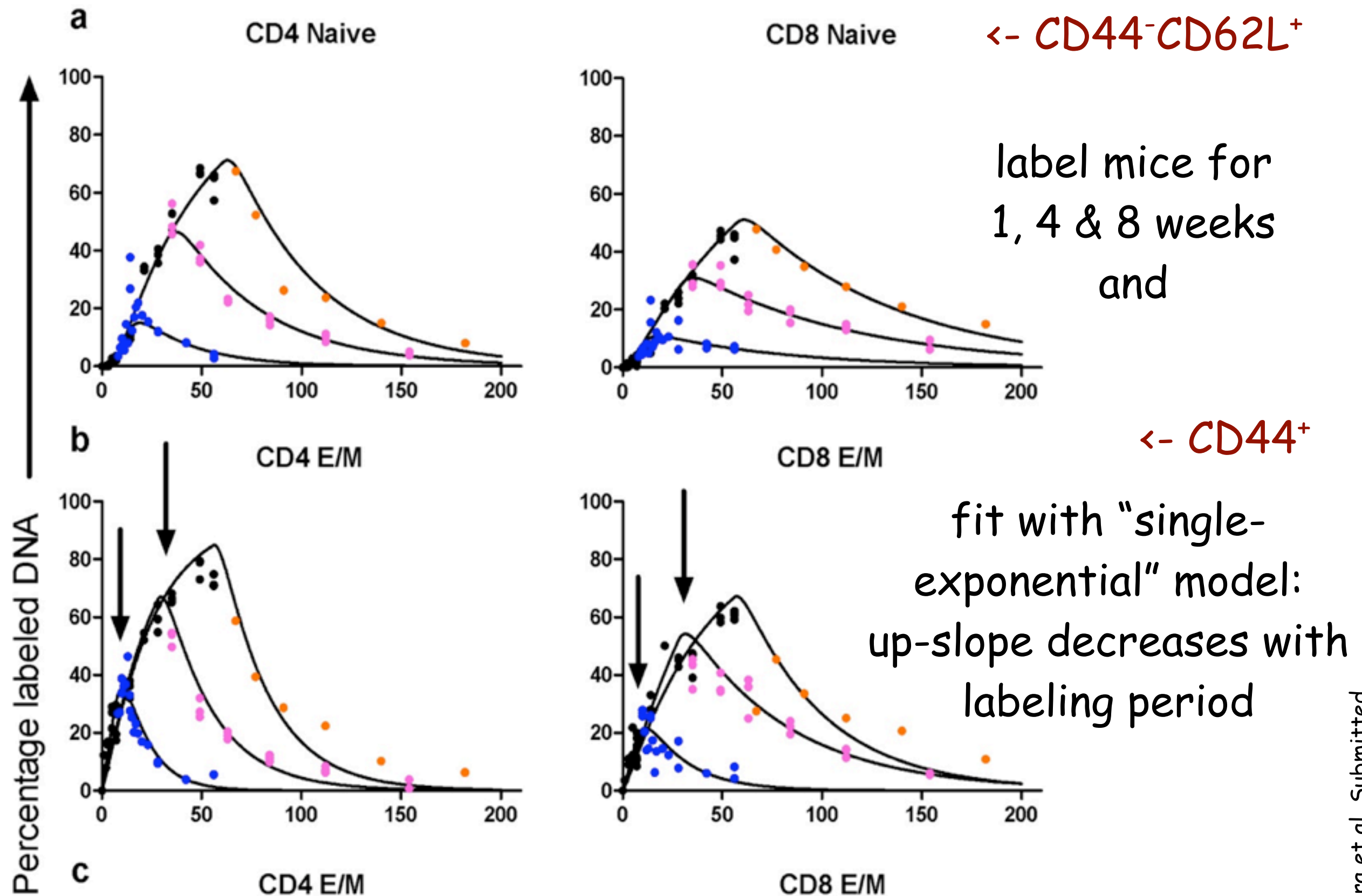
(models used by Asquith ($p = \alpha d$) and Mohri are mathematically equivalent)

So why then are the estimates of αd so different?



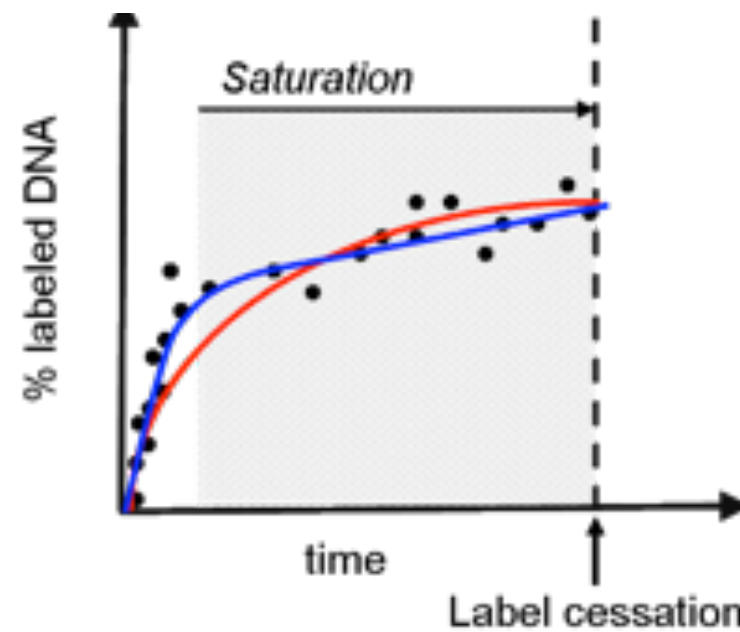
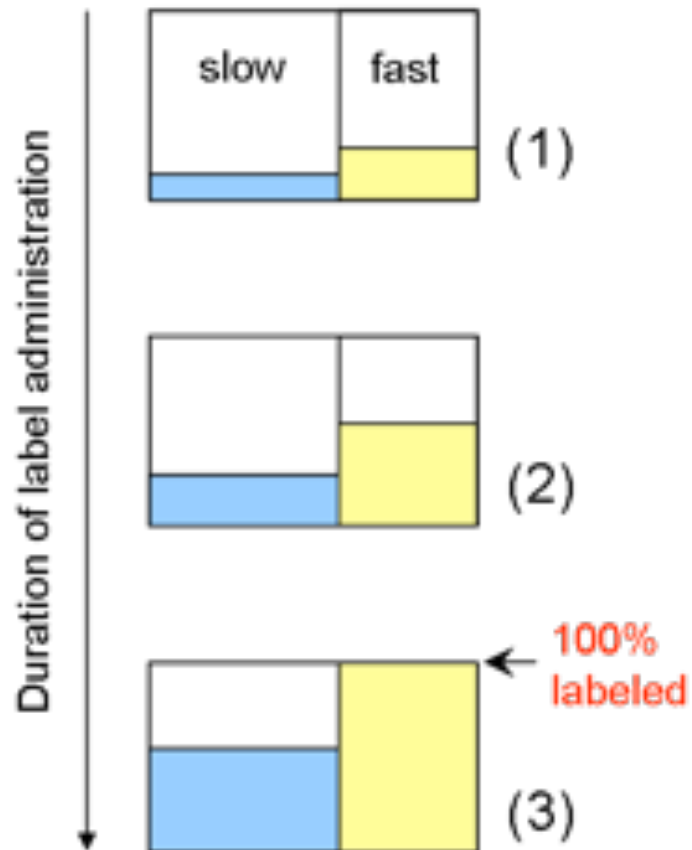
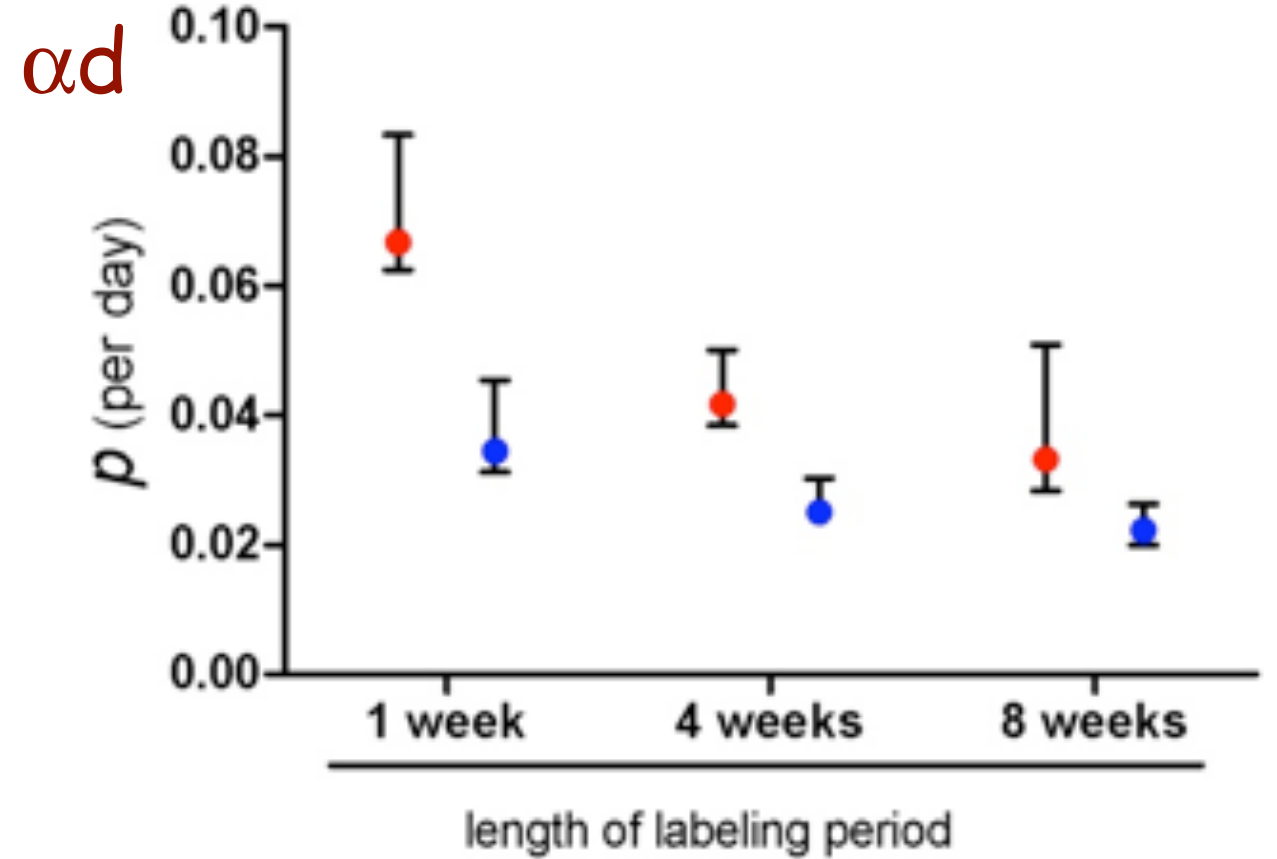
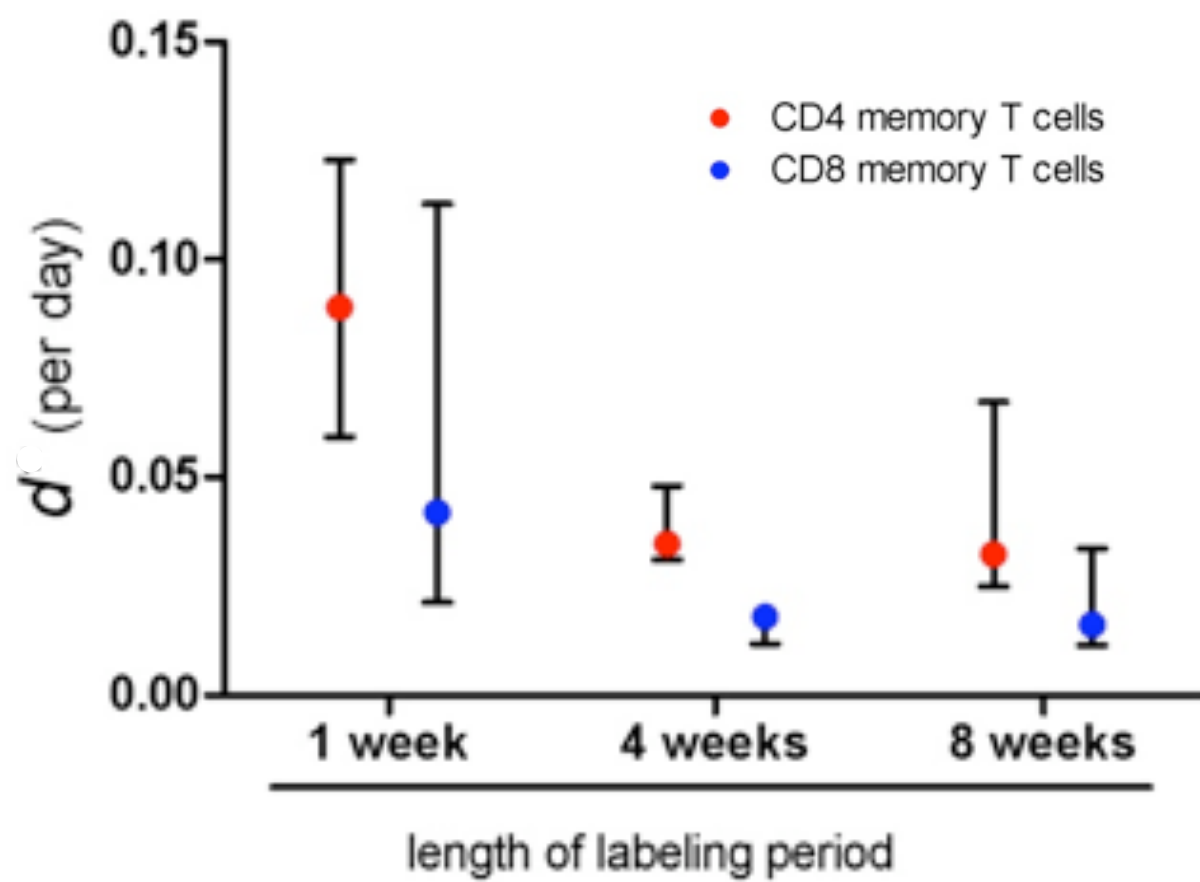
Estimates of d
are expected to
be different
[Asquith TI02]

Repeat the effect of labeling period in one experiment



While there can only be one true up-labeling curve

Memory T cells form a kinetically heterogeneous population



- Enrichment measurement
- Saturation of fastest subpopulation
- Best fit single exponential model
- Best fit multi-turnover model

Heterogeneity cannot be captured by single exponential models: compromise at long labeling periods

Generalize into explicit kinetic heterogeneity model

From

$$L(t) = \begin{cases} \alpha(1 - e^{-dt}) , & \text{if } t \leq T_{\text{end}} , \\ L(T_{\text{end}})e^{-d(t-T_{\text{end}})} , & \text{otherwise ,} \end{cases}$$

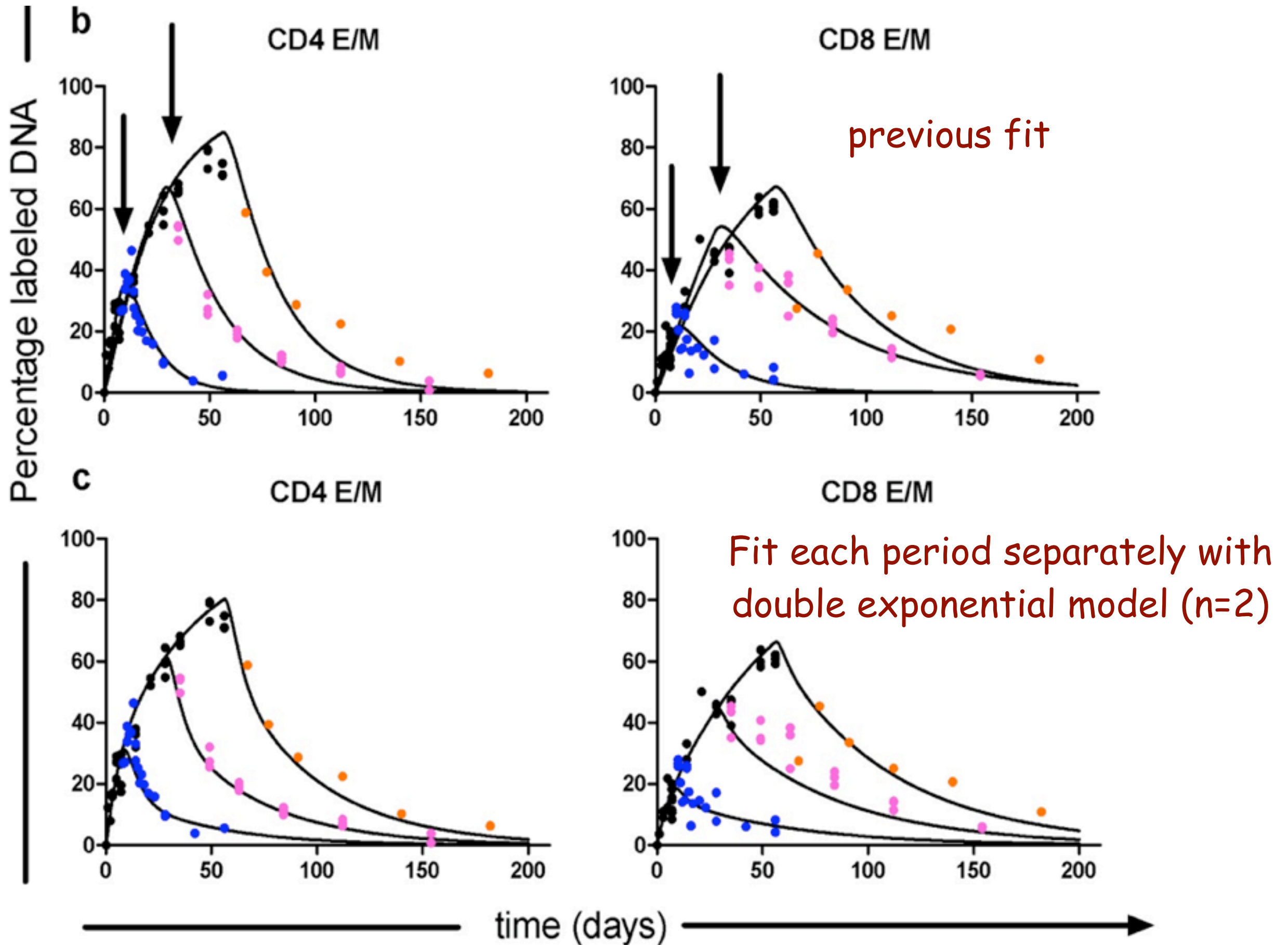
to

$$L(t) = \begin{cases} \sum \alpha_i(1 - e^{-d_i t}) , & \text{if } t \leq T_{\text{end}} , \\ \sum \alpha_i(1 - e^{-d_i T_{\text{end}}})e^{-d_i(t-T_{\text{end}})} , & \text{otherwise ,} \end{cases}$$

where α_i is the fraction of cells with turnover rate d_i

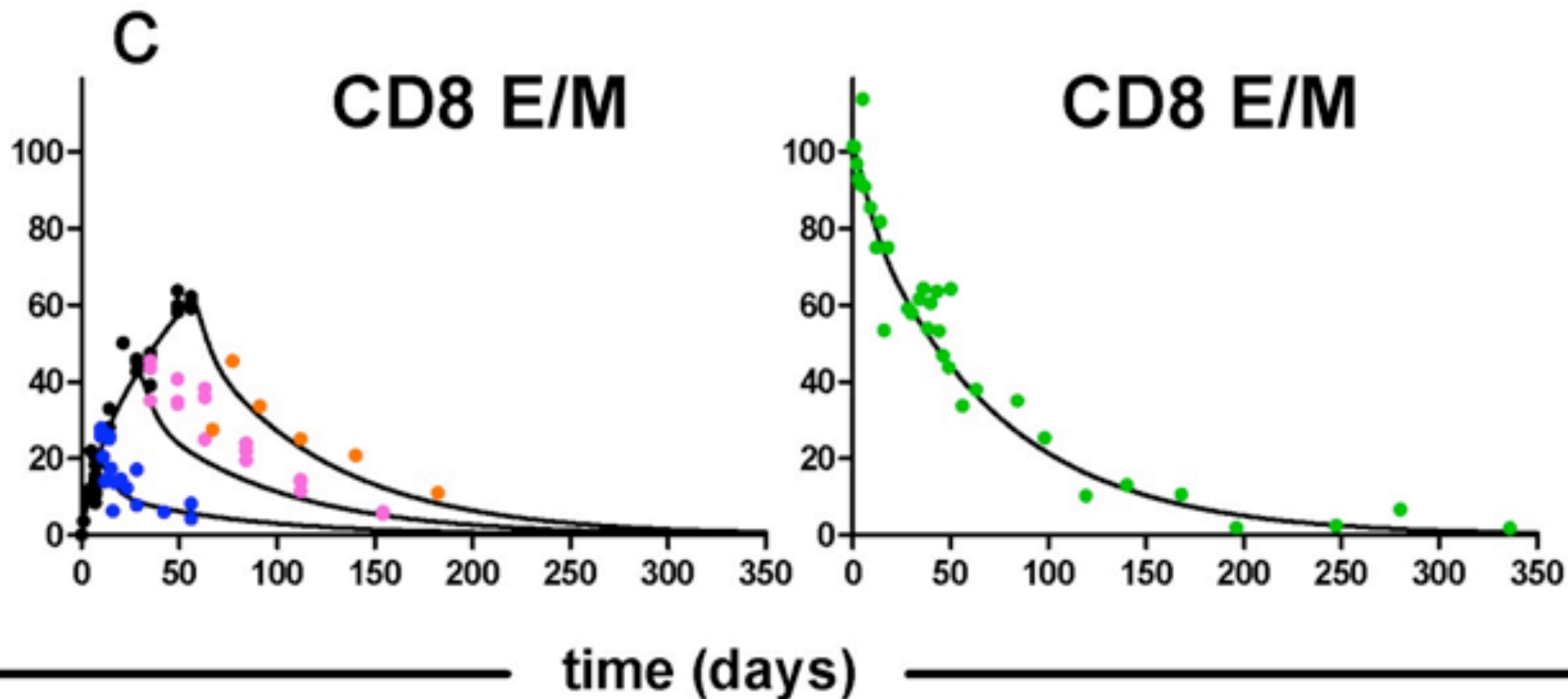
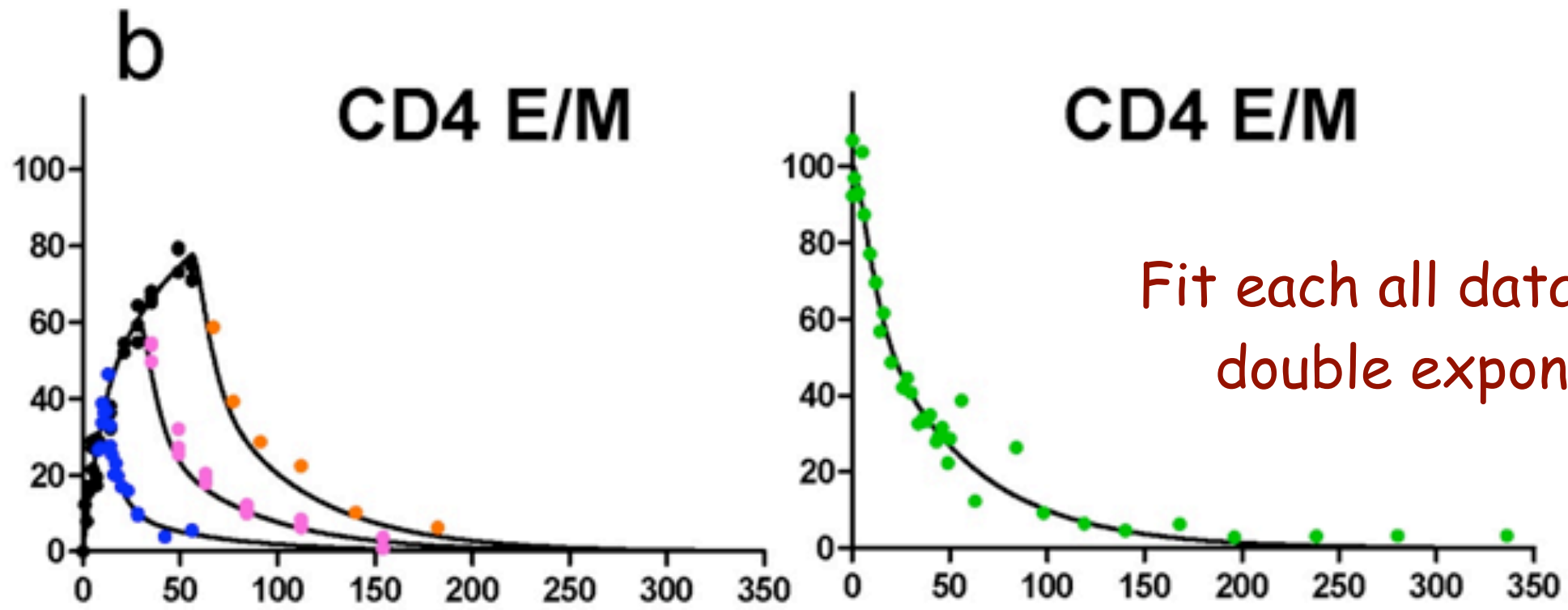
Fit model for $n = 1, 2, ..$ compartments until increasing the number of compartments no longer changes the estimated average turnover rate $d = \sum \alpha_i d_i$

Bi-phasic labeling curves call for more exponentials

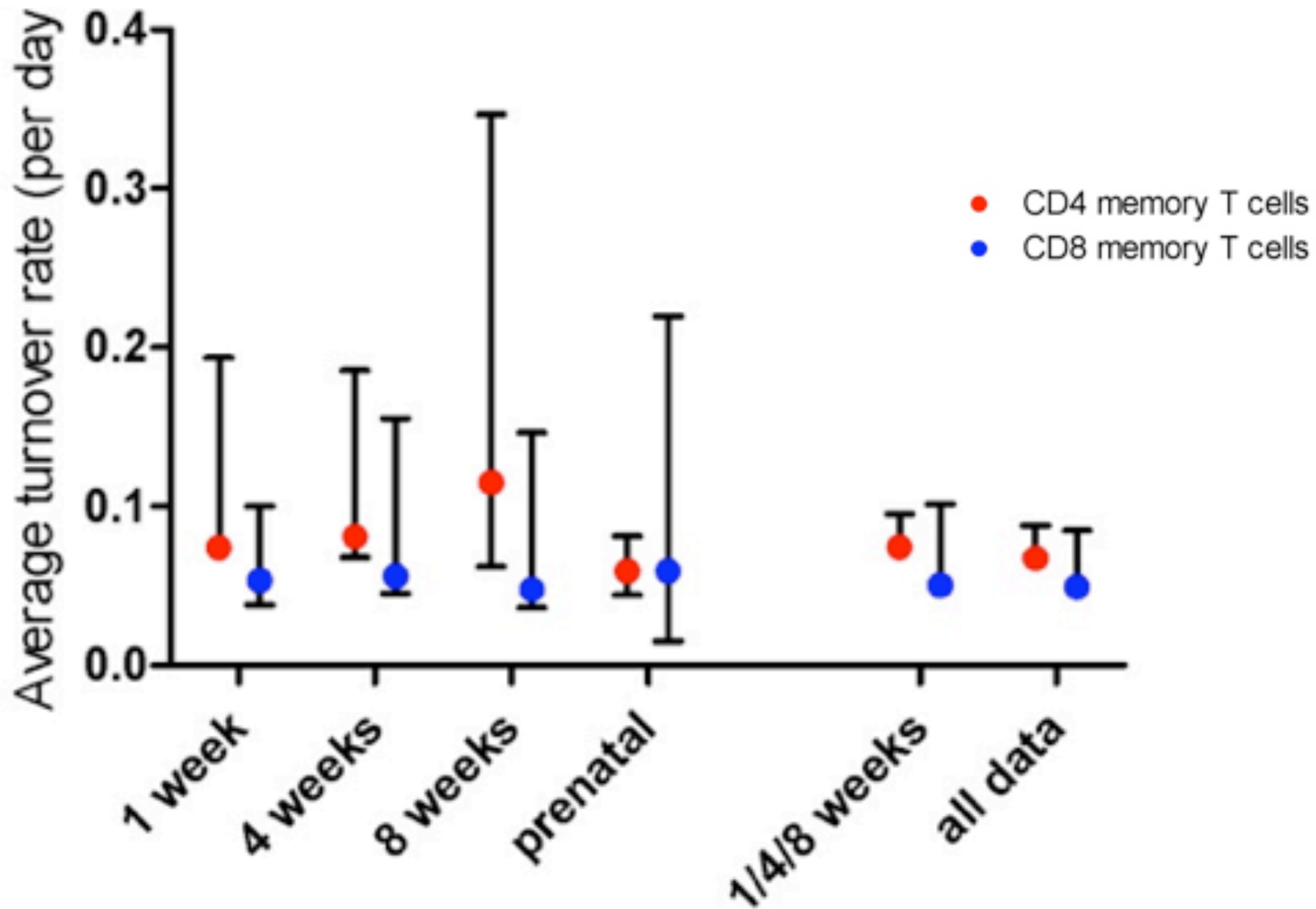


Bi-exponential model also describes prenatal labeling

Percentage labeled DNA



Fit all mouse data together with double exponential model



CD4 E/M T cells: 15 days (11.4-15.4)

CD8 E/M T cells: 20 days (11.7-22.4)

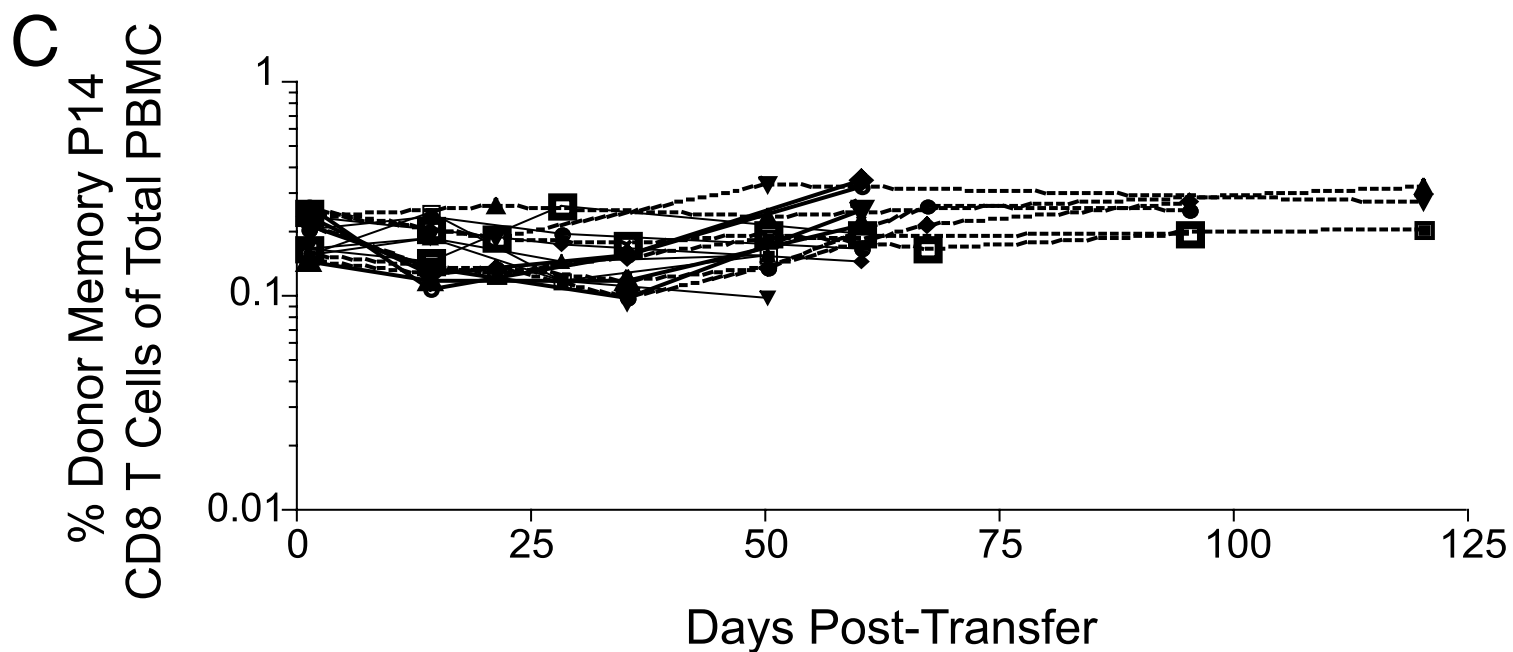
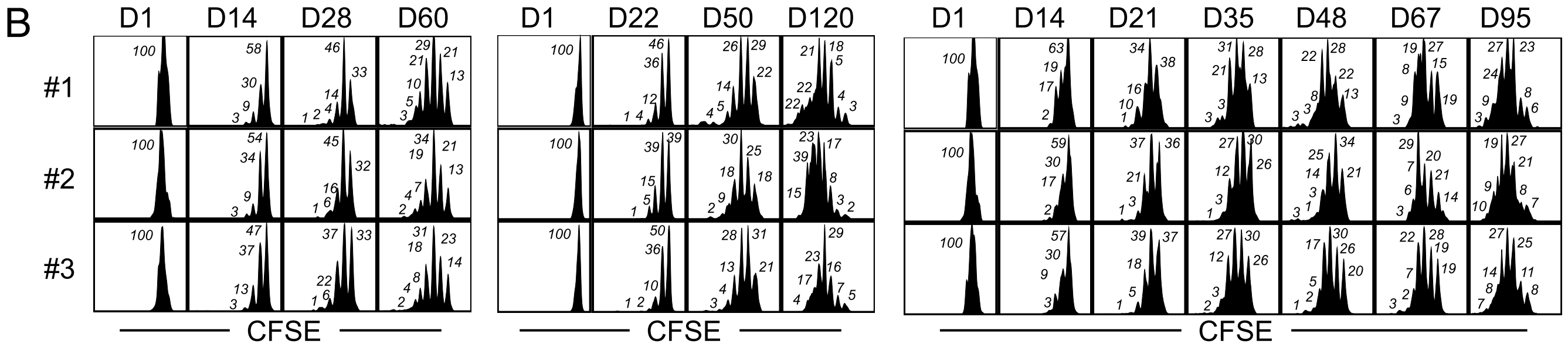
CD4 naive T cells: 50 days (48-53); CD8 naive T cells: 102 days (92-110)

But "true" memory cells live 50 days?

Homeostatic Turnover of Virus-Specific Memory CD8 T Cells Occurs Stochastically and Is Independent of CD4 T Cell Help

The Journal of Immunology 2010

Daniel K. Choo,* Kaja Murali-Krishna,† Rustom Anita,‡ and Rafi Ahmed*



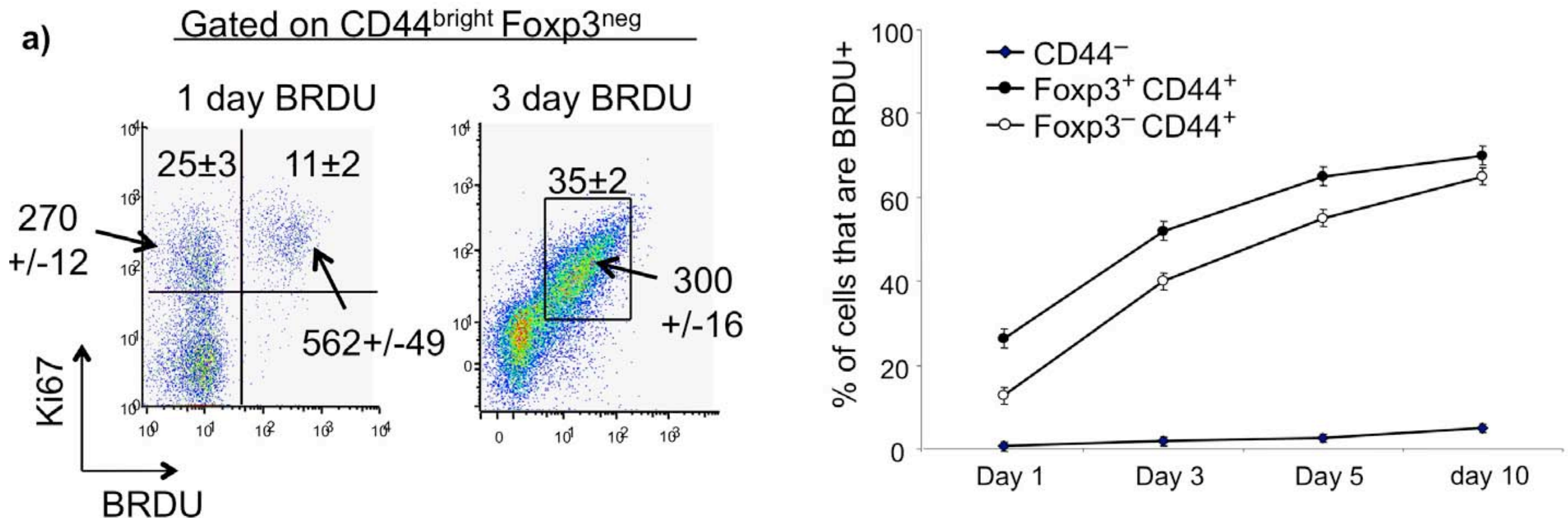
$$x_n = f_n e^{(\lambda - d)t}$$

$$f_n = \frac{(2\lambda t)^n e^{-(2\lambda t)}}{n!}$$

LCMV specific memory CD8+ T cells divide once every 50 days

Memory Phenotype CD4 T Cells Undergoing Rapid, Nonburst-Like, Cytokine-Driven Proliferation Can Be Distinguished from Antigen-Experienced Memory Cells

Souheil-Antoine Younes, George Punkosdy, Stephane Caucheteux, Tao Chen, Zvi Grossman, William E. Paul*



Combining BrdU and Ki67:

LCMV specific CD4⁺ T cells divide once every 50 days while other CD44⁺ memory cells divide every 2-3 weeks

Conclusions on T cell kinetics in mice

Life span	Range	T cell type	Method	Model	Ref.	Remarks
mouse						
68 d	65–71 d	CI	naive CD8 ⁺	BrdU	Eq. (13)	Parretta <i>et al.</i> [172] thymectomized mice
47 d	41–54 d	CI	naive CD4 ⁺	² H ₂ O	Eq. (23)	Den Braber <i>et al.</i> [56] young adult mice
80 d	67–92 d	CI	naive CD8 ⁺	² H ₂ O	Eq. (23)	Den Braber <i>et al.</i> [56] young adult mice
41 d	36–47 d	CI	naive CD4 ⁺	² H ₂ O	Eq. (23)	Den Braber <i>et al.</i> [56] old mice
116 d	94–139 d	CI	naive CD8 ⁺	² H ₂ O	Eq. (23)	Den Braber <i>et al.</i> [56] old mice
90 d	64–133 d	CI	memory CD8 ⁺	BrdU	Eq. (18)	Parretta <i>et al.</i> [172] no source: $\sigma = 0$, no de-labeling
50 d	—		memory CD8 ⁺	CFSE	Eq. (15)	Choo <i>et al.</i> [35] LCMV specific memory cells
14–22 d	—		memory CD4 ⁺	BrdU	*	Younes <i>et al.</i> [238] memory phenotype cells
50 d	—		memory CD4 ⁺	Ki67	—	Younes <i>et al.</i> [238] LCMV specific memory cells
15 d	11–15 d	CI	memory CD4 ⁺	² H ₂ O	Eq. (26)	Westera <i>et al.</i> [226] 3 different labeling periods
20 d	12–22 d	CI	memory CD8 ⁺	² H ₂ O	Eq. (26)	Westera <i>et al.</i> [226] 3 different labeling periods

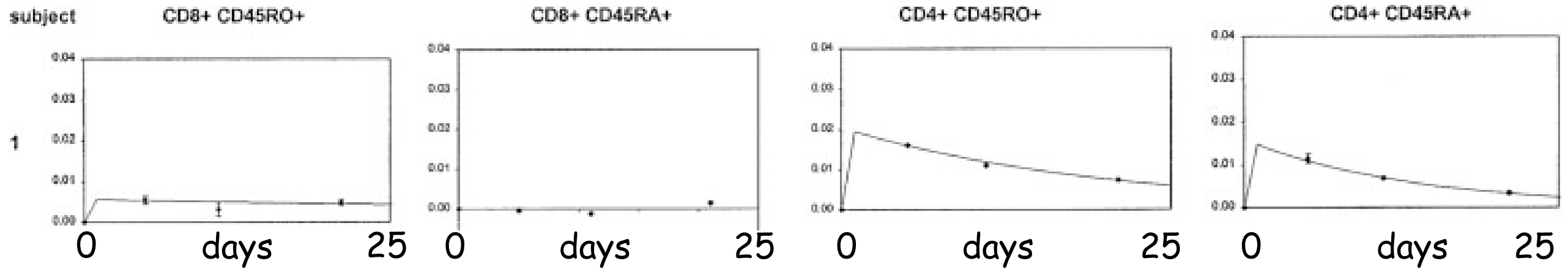
Memory phenotype cells turn over faster than "true" memory T cells?

Naive T cells live longer than memory T cells.

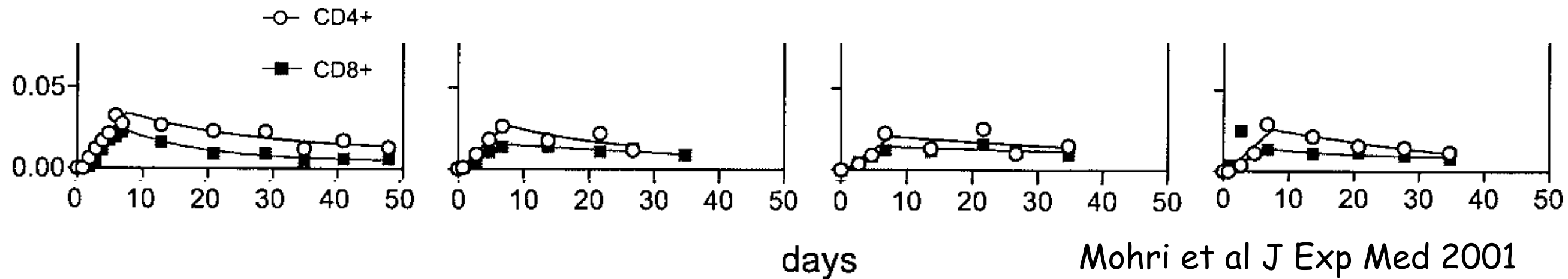
CD8⁺ naive T cells live longer than CD4⁺ naive T cells.

Back to the kinetics of human T cells

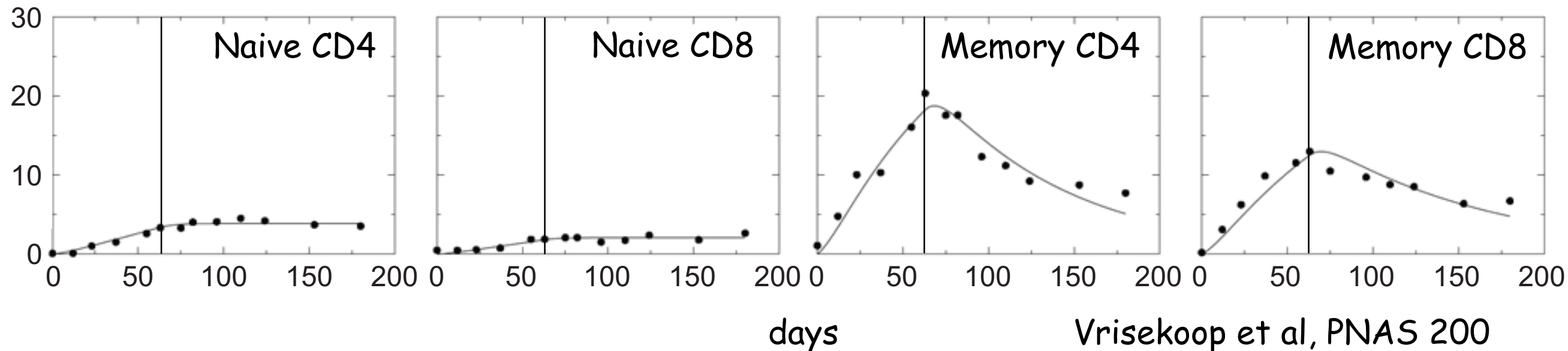
Enrichment



Enrichment



Enrichment (%)

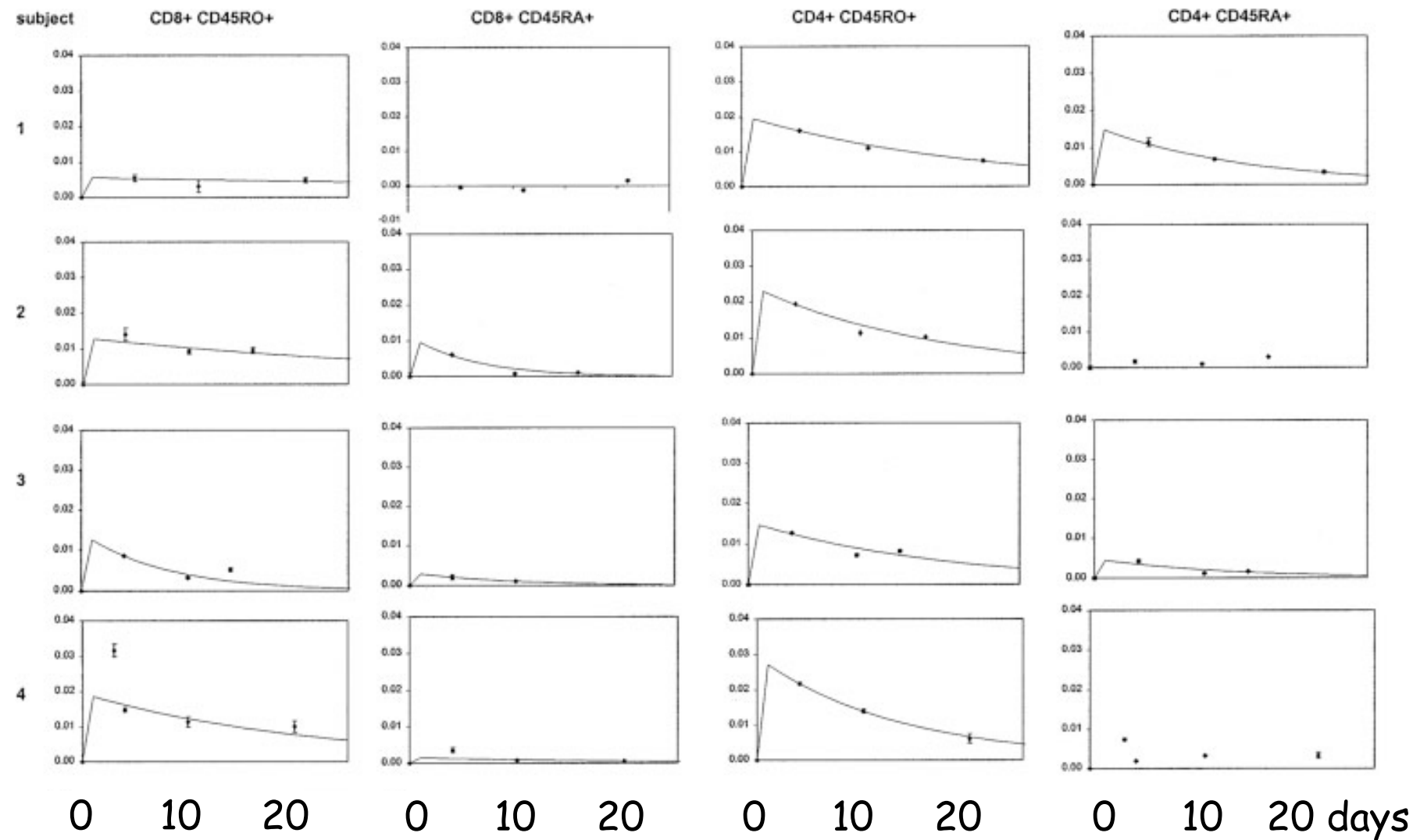


Short studies D-glucose and long study D-water

Very short term labeling with glucose also problematic

2318 D.C. Macallan et al.

Eur. J. Immunol. 2003. 33: 2316–2326



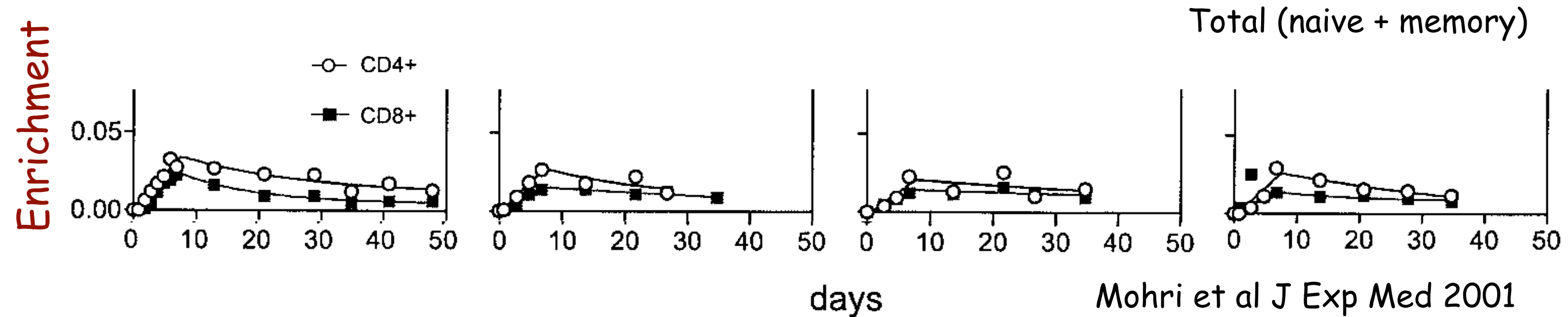
One day of labeling: but “peak” observed only at day three.

Assume true peak at day one and extrapolate down-slope backwards to back-calculate true peak at day 1.

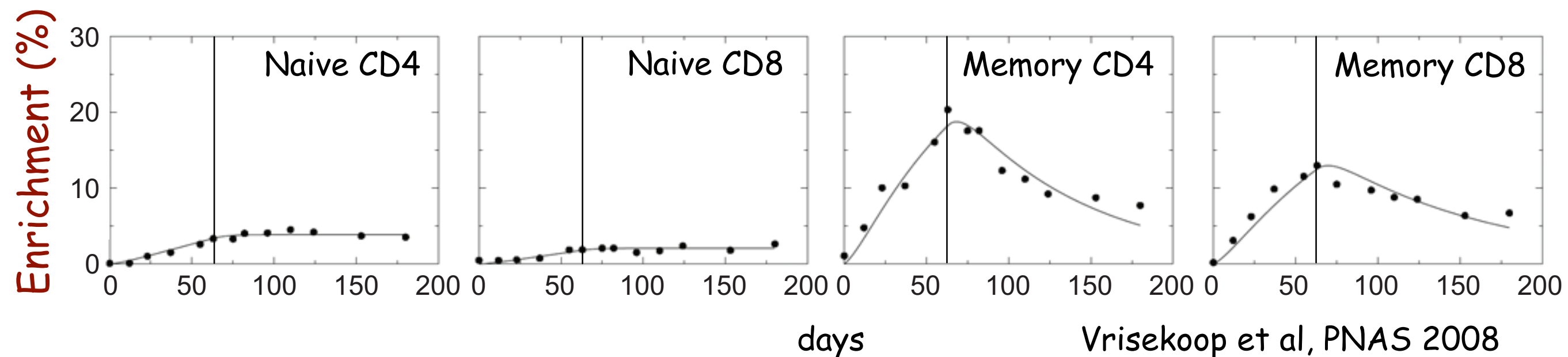
Short term labeling suffers from unknown exit rates from lymphoid tissue to blood and poorly estimates initial up-slope.

Life spans remain different between two long-term studies

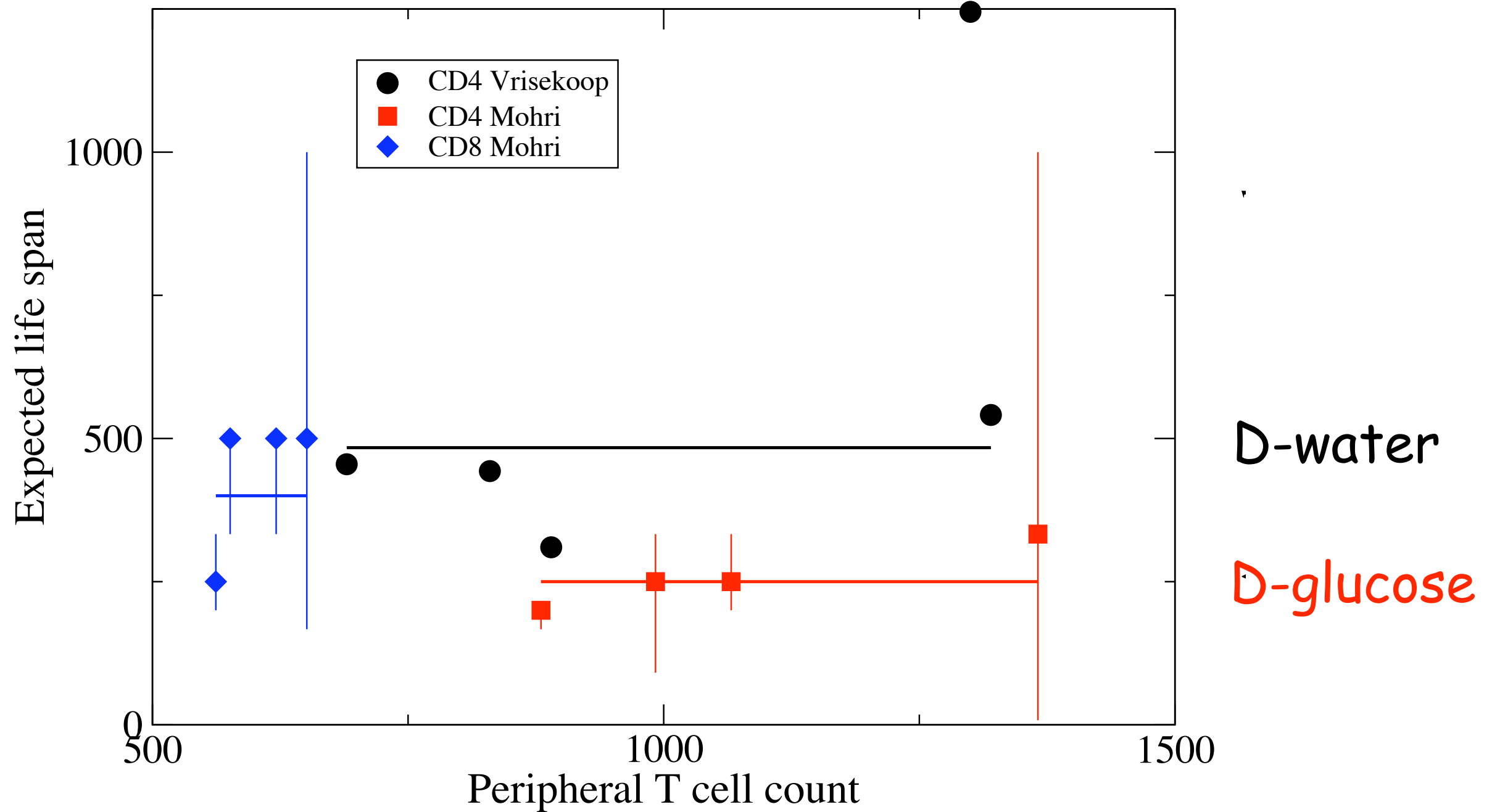
7 days D-glucose



9 weeks D-water



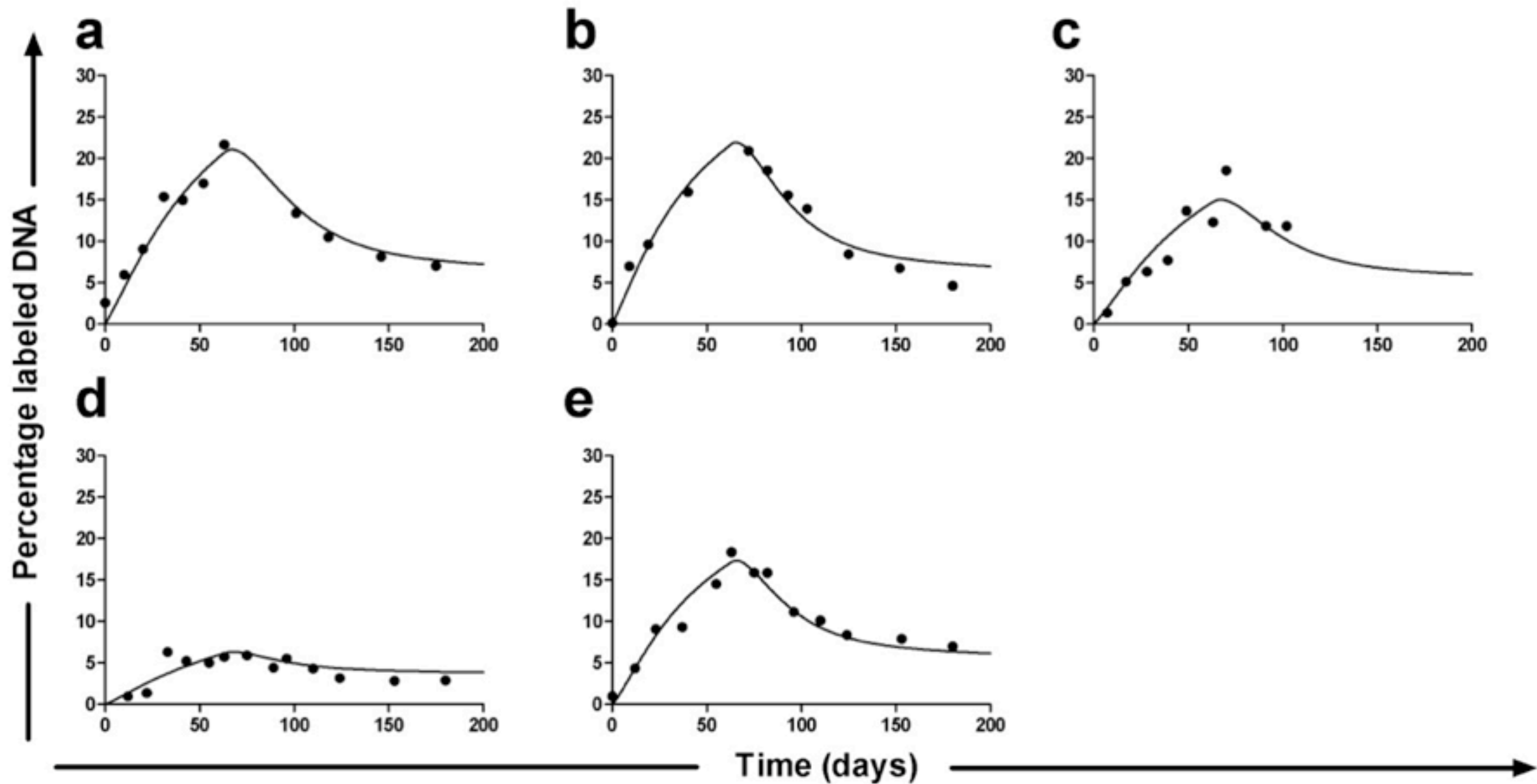
Published expected life spans of human CD4⁺ T cells



Vrisekoop naive & memory data were recalculated into total CD4

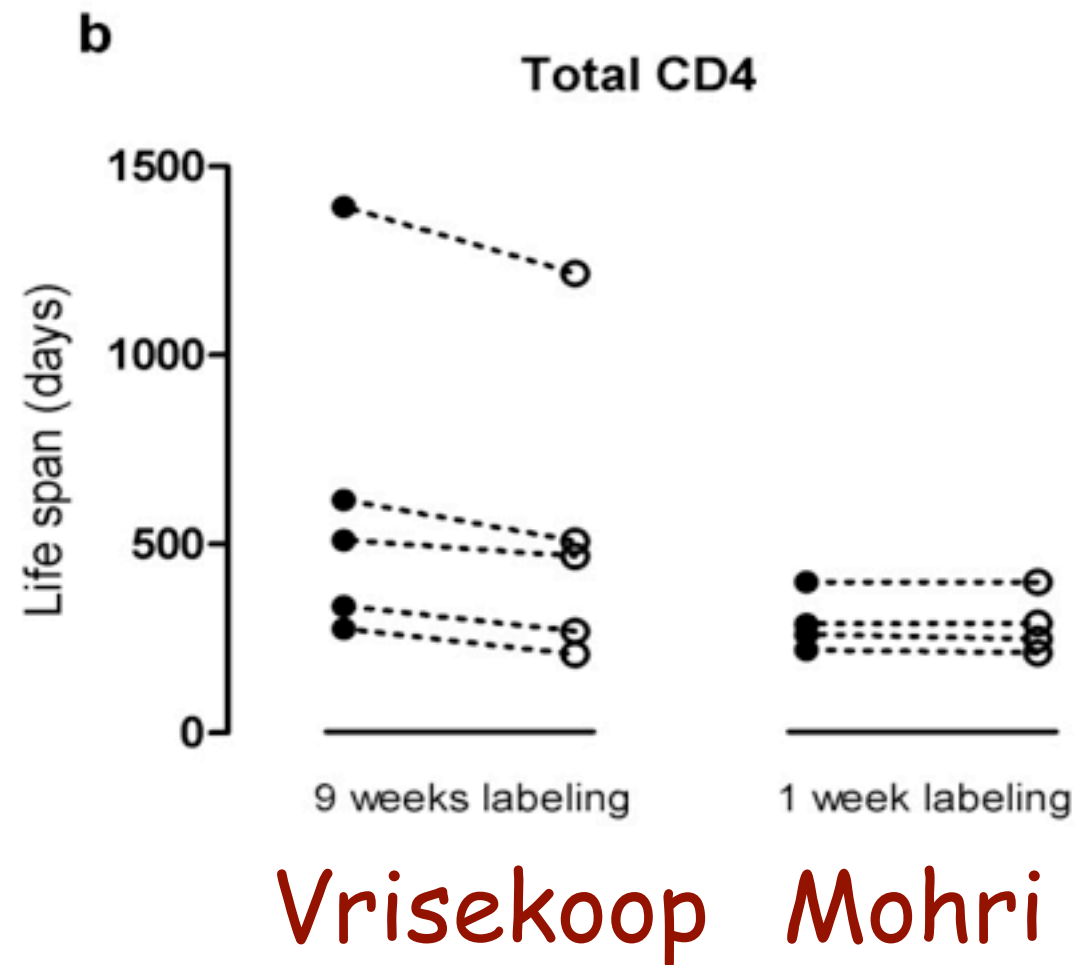
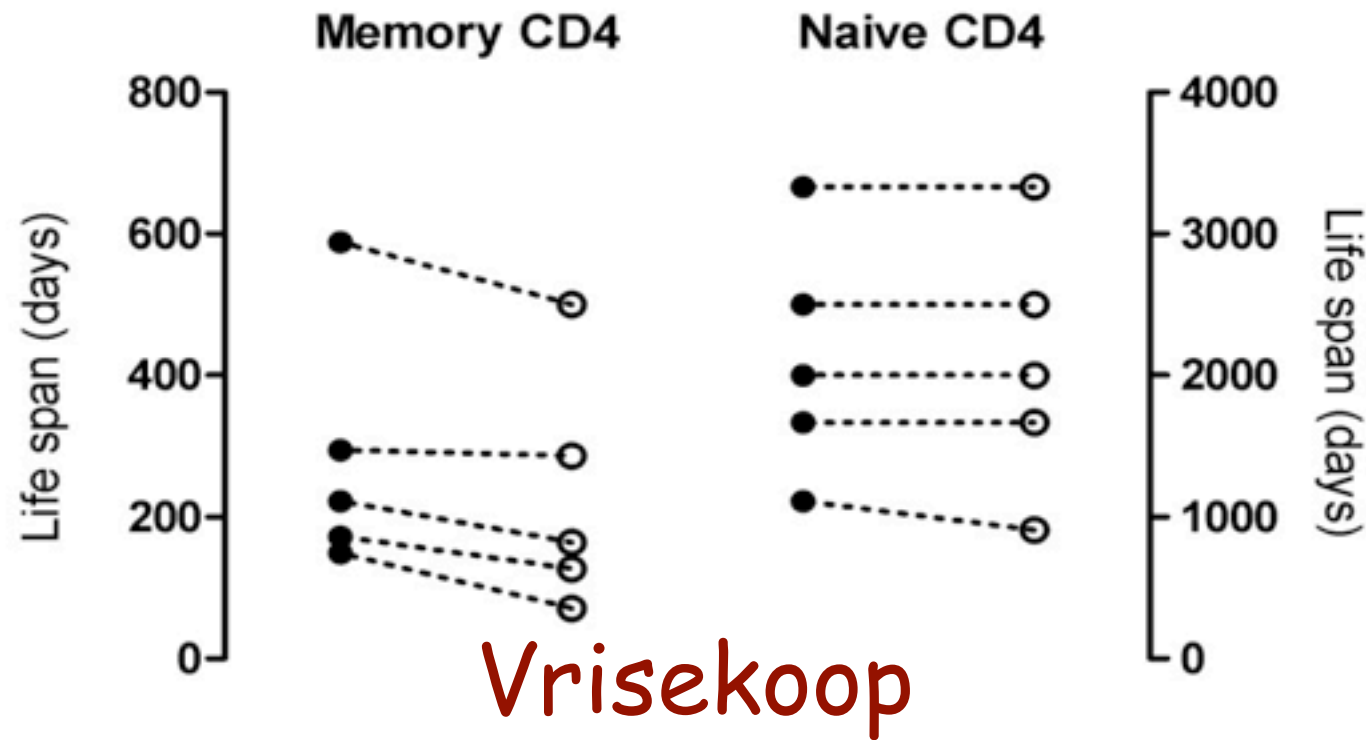
Mohri (JEM 2001): 1 week D-glucose & Vrisekoop (PNAS 2008): 9 weeks D-water

Refit both data sets using double exponent models



Memory $CD4^+$ T cells from Vrisekoop (PNAS 2008): fits significantly better than original model

Shorter life spans using double exponent models



- single exponential
- double exponential

Difference between Mohri and Vrisekoop becomes smaller

Conclusions from 5 human volunteers labeled with D-water

Expected life spans (medians)

Naive CD4⁺ T cells: 2000 days (5.5 years)

Naive CD8⁺ T cells: 3300 days (9.1 years)

Effector/memory CD4⁺ T cells: 160 days (0.45 years)

Effector/memory CD8⁺ T cells: 160 days (0.45 years)

Compartments:

Naive T cell data typically requires only one exponent

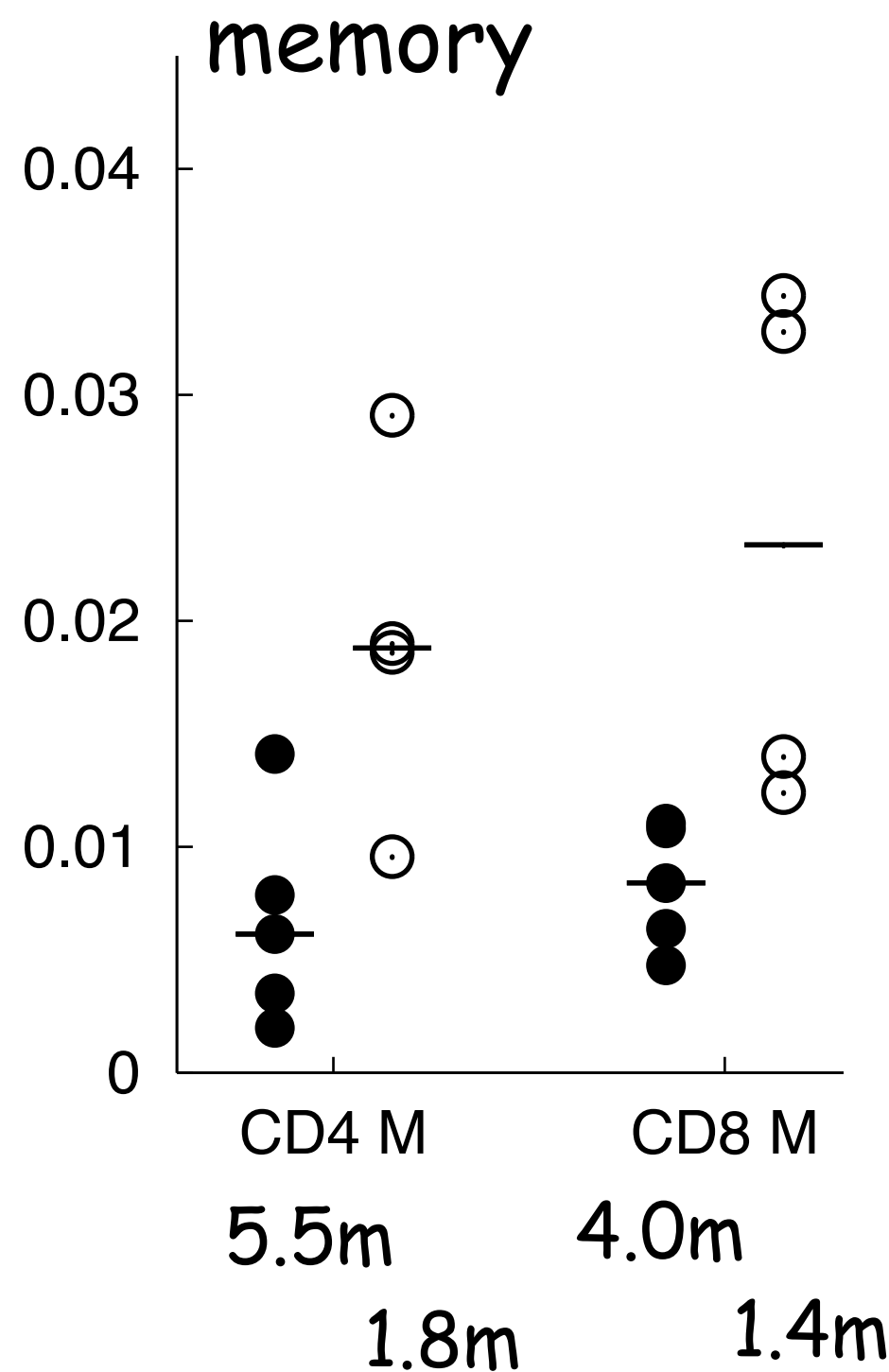
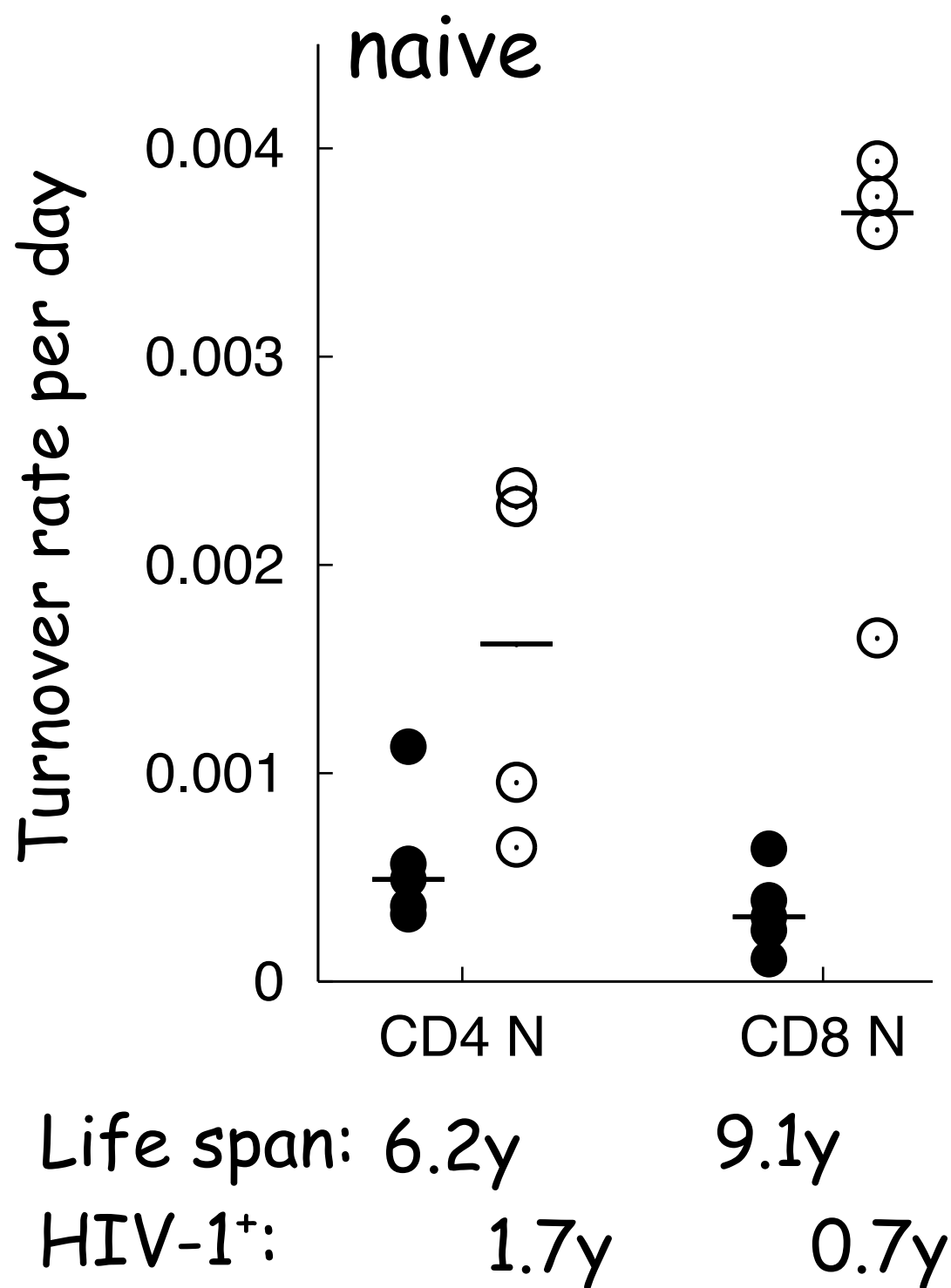
Memory data do require 2 compartments: heterogeneity

Immunological memory is maintained by short-lived cells

Vrisekoop et al PNAS 2008

Westera et al Submitted

5 human volunteers (●) and 4 HIV-1⁺ Patients (⊙)

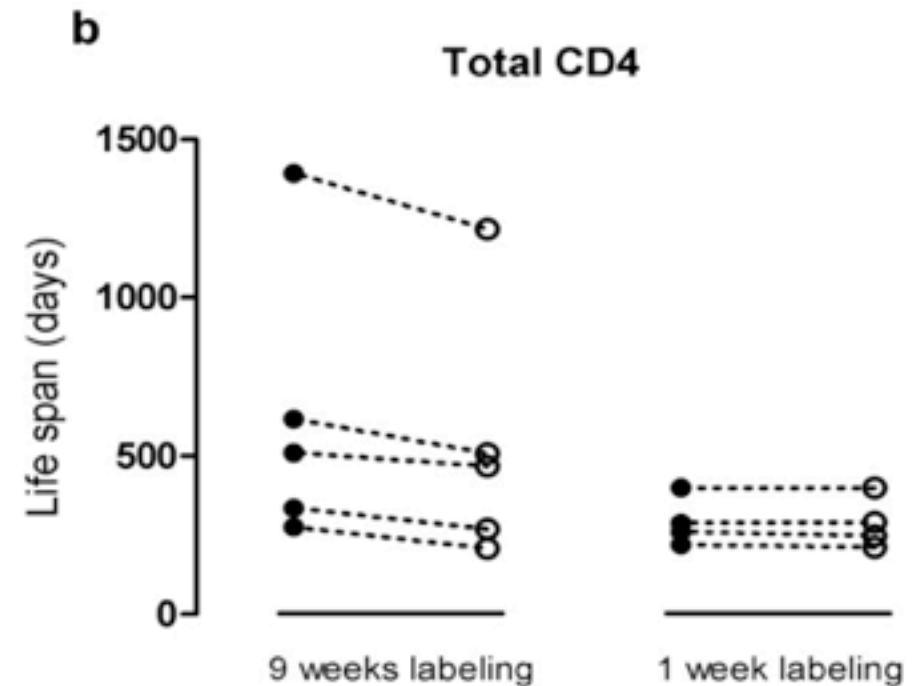


HIV-1 infection increases cellular turnover rates (production)

Fitted with a single exponential model

some problems remain ...

Is the difference between
D-glucose and D-water
really solved?



Also differences between the 2 day and the 1 week glucose data
(to be worked on here with Becca Asquith)

Biology of the n-compartment model should not be
taken too seriously

Kinetic vs Temporal heterogeneity

Modelling deuterium labelling of lymphocytes with temporal and/or kinetic heterogeneity

Rob J. De Boer^{1,3,*}, Alan S. Perelson^{2,3} and Ruy M. Ribeiro²

Model with resting and recently divided cells:

$$\left. \begin{aligned} \frac{dR}{dt} &= rA - (a + d_R)R \\ \frac{dA}{dt} &= caR - (r + d_A)A. \end{aligned} \right\}$$

$c=2$ models the
Choo et al LCMV CFSE data.
Typically $d_A > d_R$

One can find a solution:

$$\left. \begin{aligned} \frac{dU_R}{dt} &= rU_A - (a + d_R)U_R \\ \frac{dU_A}{dt} &= aU_R - (r + d_A)U_A \end{aligned} \right\}, \quad \begin{aligned} L(t) &= 1 - \alpha e^{-e_1 t} - (1 - \alpha)e^{-e_2 t}, \\ L(t) &\simeq \alpha(1 - e^{-e_1 t_{\text{end}}})e^{-e_1(t - t_{\text{end}})} \\ &\quad + (1 - \alpha)(1 - e^{-e_2 t_{\text{end}}})e^{-e_2(t - t_{\text{end}})}, \end{aligned}$$

labeling phase

de-labeling phase:

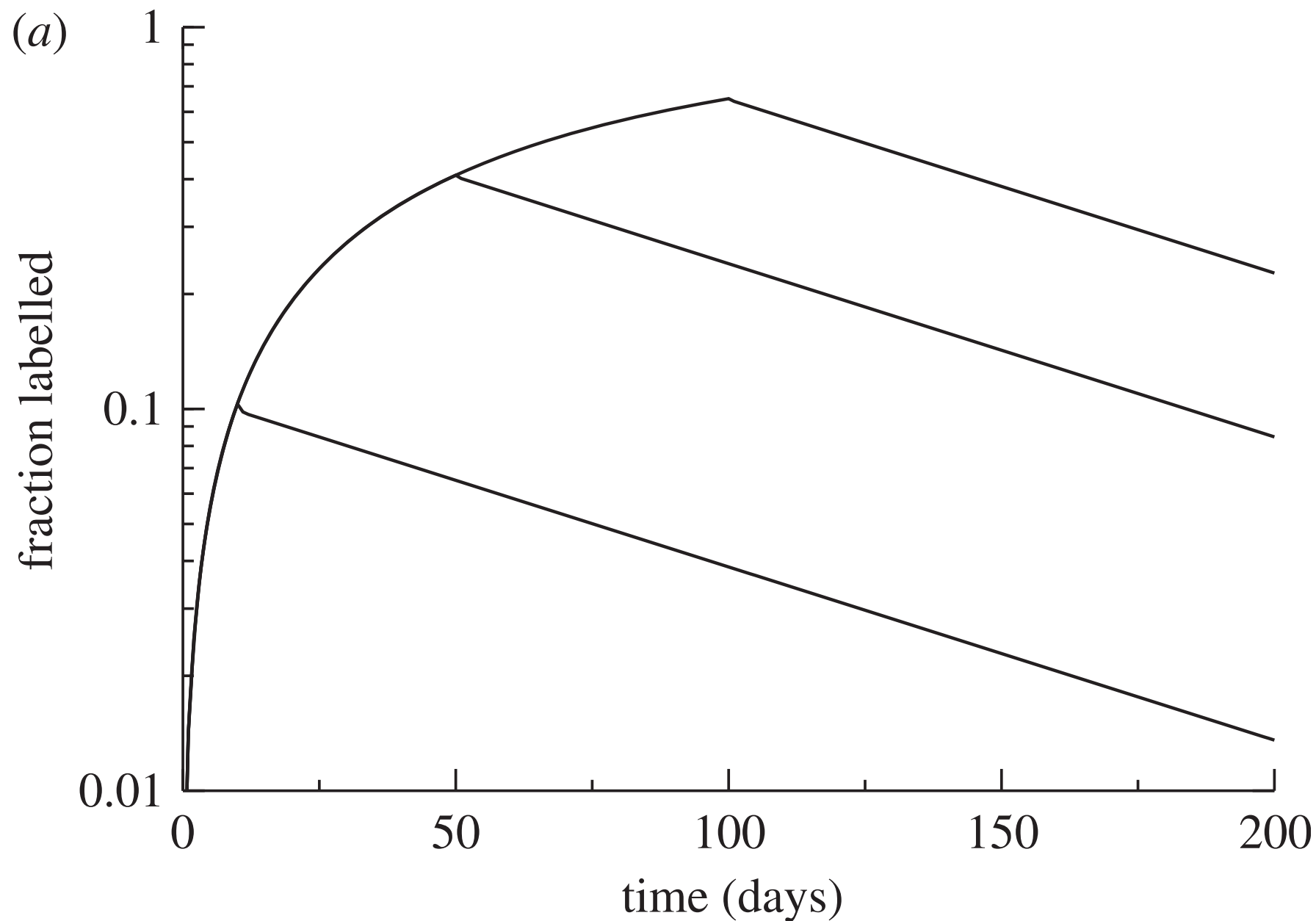
where α , e_1 and e_2 are combinations of r , a , c , d_R and d_A .

However, since this solution is very close to what we had above:

$$L(t) = \begin{cases} \sum \alpha_i (1 - e^{-d_i t}), & \text{if } t \leq T_{\text{end}}, \\ \sum \alpha_i (1 - e^{-d_i T_{\text{end}}}) e^{-d_i (t - T_{\text{end}})}, & \text{otherwise,} \end{cases}$$

both models fit the data equally well. Thus, one can no longer interpret their parameters biologically.

Create D-water data using the LCMV parameters



$$\frac{dR}{dt} = rA - (a + d_R)R$$

$$\frac{dA}{dt} = caR - (r + d_A)A.$$

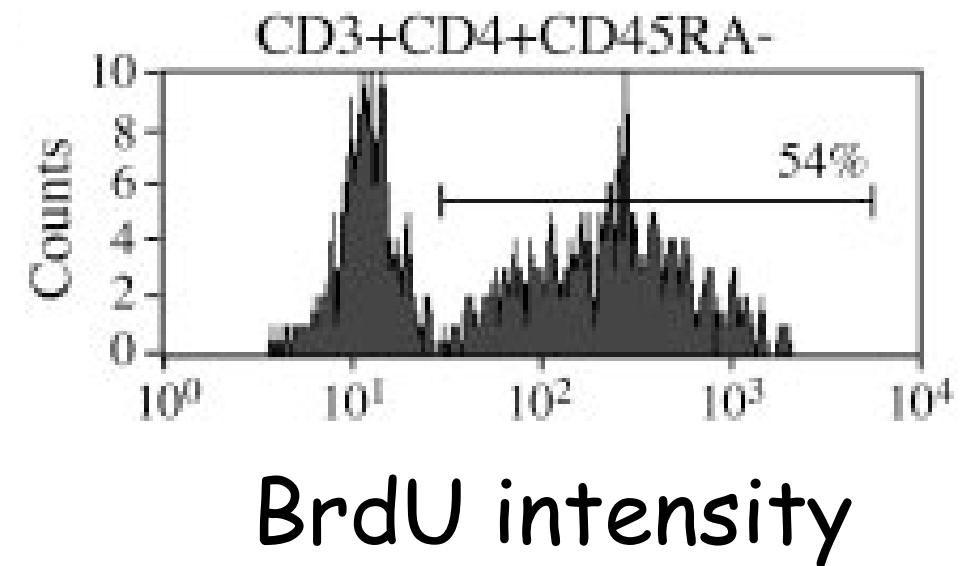
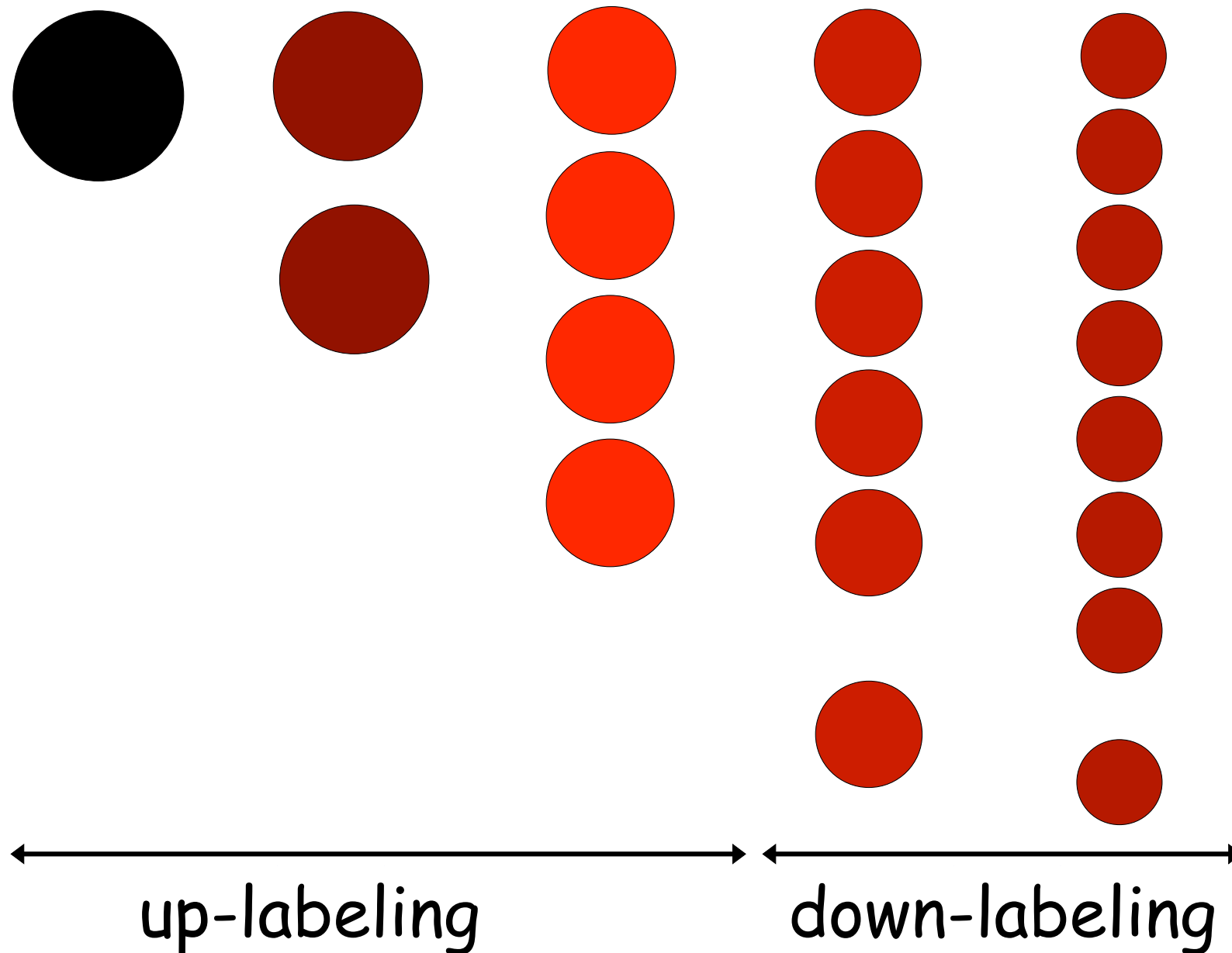
$$a = 0.02\text{d}^{-1}$$

$$d_R = 0.001\text{d}^{-1}$$

$$d_A = 1\text{d}^{-1}$$

If this data is fitted with either of the two models, the fit is perfect but the estimated turnover rate is 2-fold off. This gets better when the average turnover rate is higher.

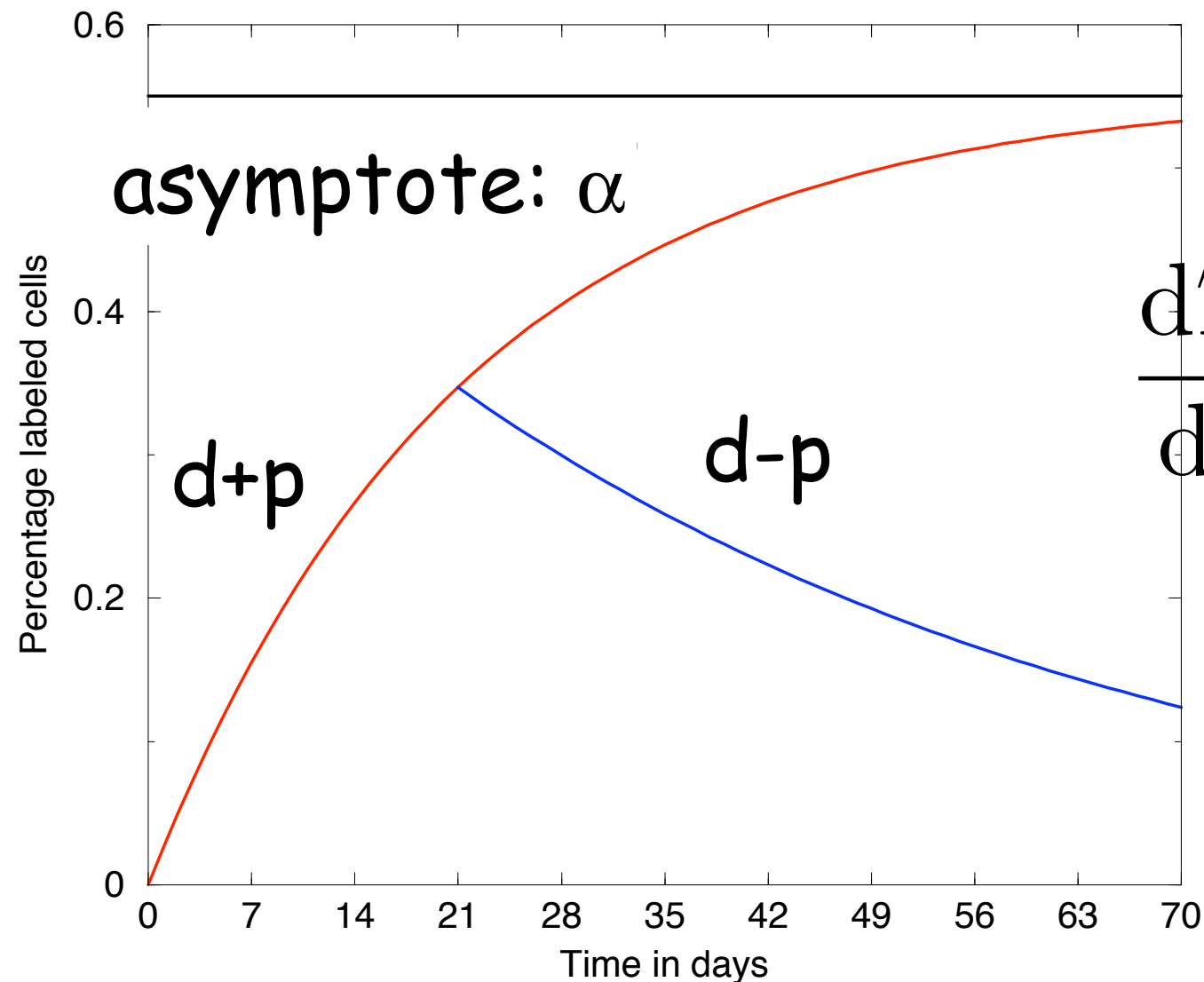
BrdU labeling



BrdU is a nucleoside analog incorporates into new DNA strands
Can be detected in cells by staining cells with an antibody.
Brightness reflects fraction of BrdU labeled DNA strands
Above some "threshold brightness" cells are coined BrdU⁺

BrdU labeling

$$L(t) = \begin{cases} \alpha(1 - e^{-(p+d)t}) & , \text{ if } t \leq T_{\text{end}} , \\ L(T_{\text{end}})e^{(p-d)(t-T_{\text{end}})} & , \text{ otherwise ,} \end{cases}$$



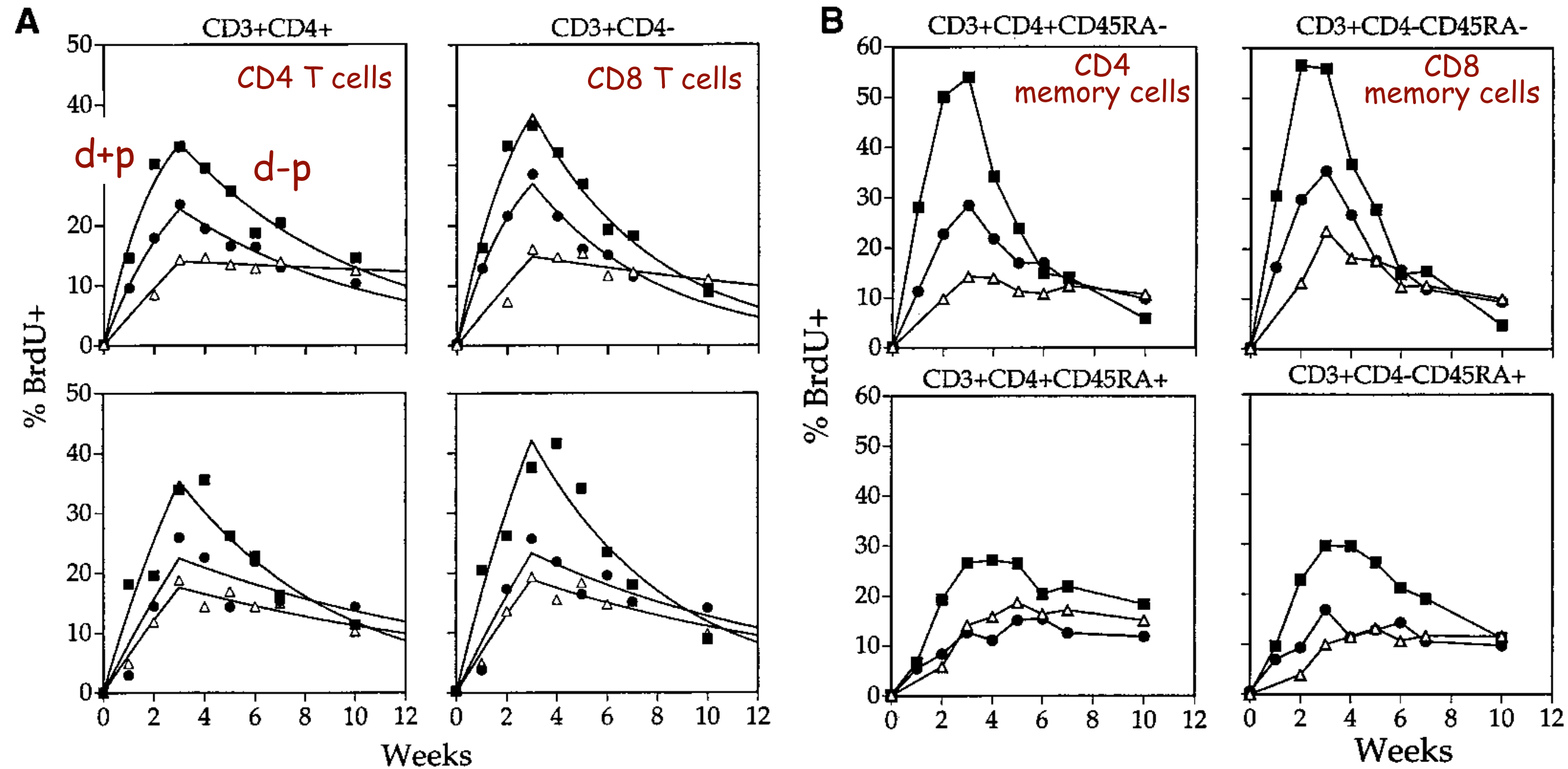
$$\frac{dT}{dt} = s + (p - d)T = 0$$

Labeling:
one cell \rightarrow two labeled cells

De-labeling:
one labeled cell \rightarrow two labeled cells

Self-renewing population at steady state ($s=0$, $p=d$)
should have a zero down-slope.

The zero down-slope is a problem

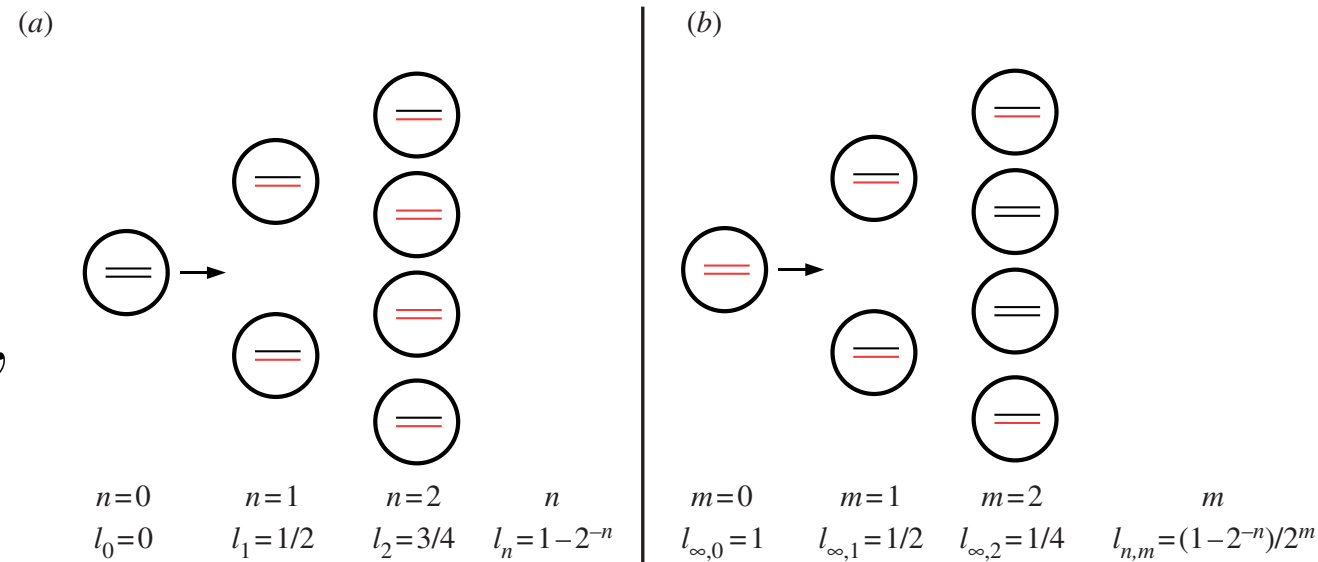


Macaques having BrdU in drinking water for 3 weeks
Uninfected (triangle) and SIV infected monkeys

Solution is to allow for BrdU dilution

$$\frac{dN_0(t)}{dt} = -(p + d)N_0(t) ,$$

$$\frac{dN_n(t)}{dt} = 2pN_{n-1}(t) - (p + d)N_n(t) ,$$



Solution with Poisson distribution

$$N_n(t) = N(t) \times \frac{(2pt)^n}{n!} e^{-2pt} = N(t) \times f_n(t, p) , \quad \leftarrow \text{labeling (T days)}$$

$$N_{n,m}(t) = N(t) \times f_n(T, p) \times f_m(t - T, p) , \quad \leftarrow \text{delabeling}$$

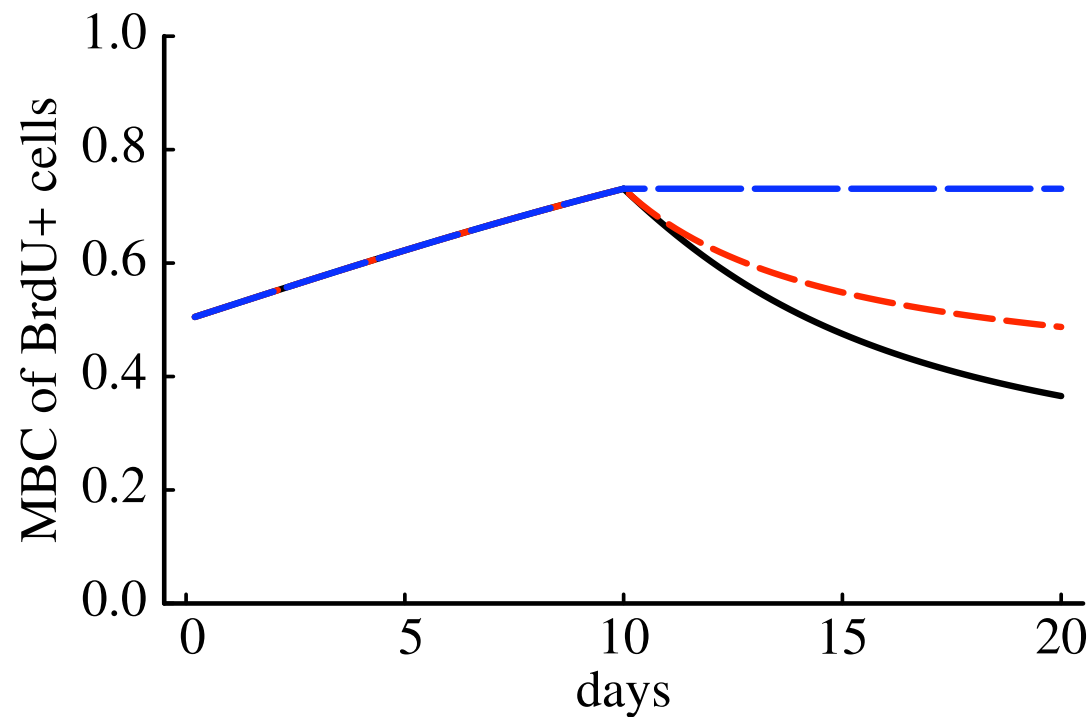
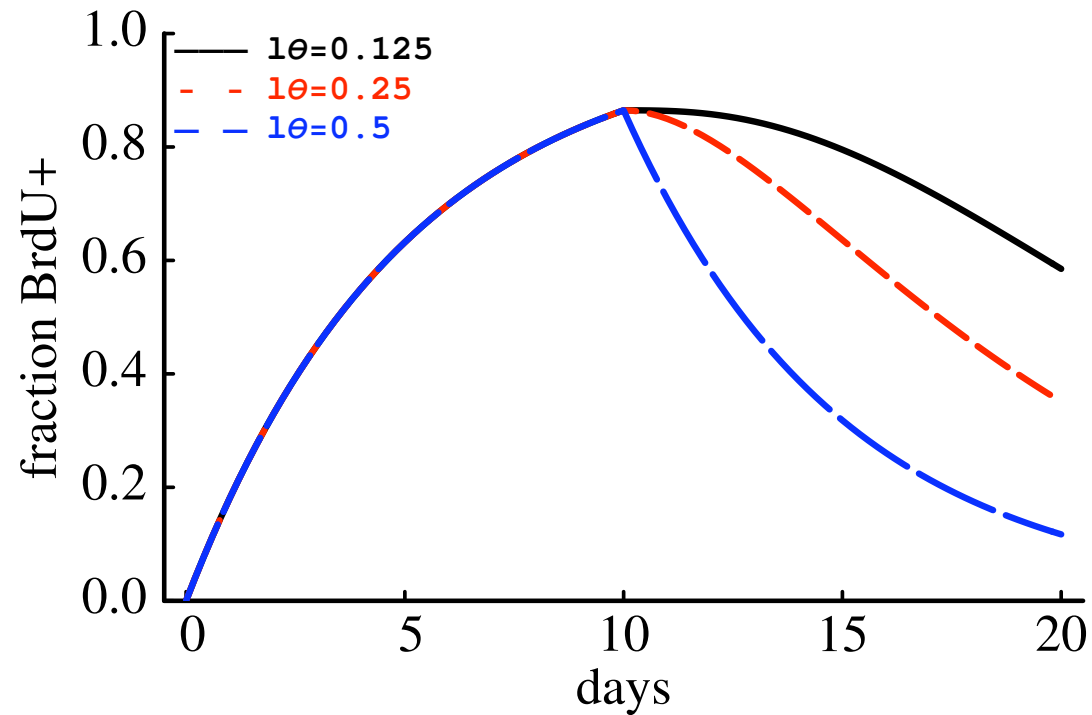
Fraction of labeled cells:

$$L(t) = \begin{cases} \sum_{n=1}^{\infty} H(l_n - l_{\theta}) \times f_n(t, p) , & \text{if } t \leq T , \\ \sum_{n=1}^{\infty} \sum_{m=1}^{\infty} H(l_{n,m} - l_{\theta}) \times f_n(T, p) \times f_m(t - T, p) , & \text{otherwise .} \end{cases}$$

$$l_n = 1 - 2^{-n} \quad l_{n,m} = (1 - 2^{-n})/2^m$$

$H(x)$ is a Heaviside function, i.e., $H(x) = 0$ whenever $x < 0$

Now we obtain a down-slope when $p=d$



Fraction BrdU⁺ cells
for 3 detection thresholds

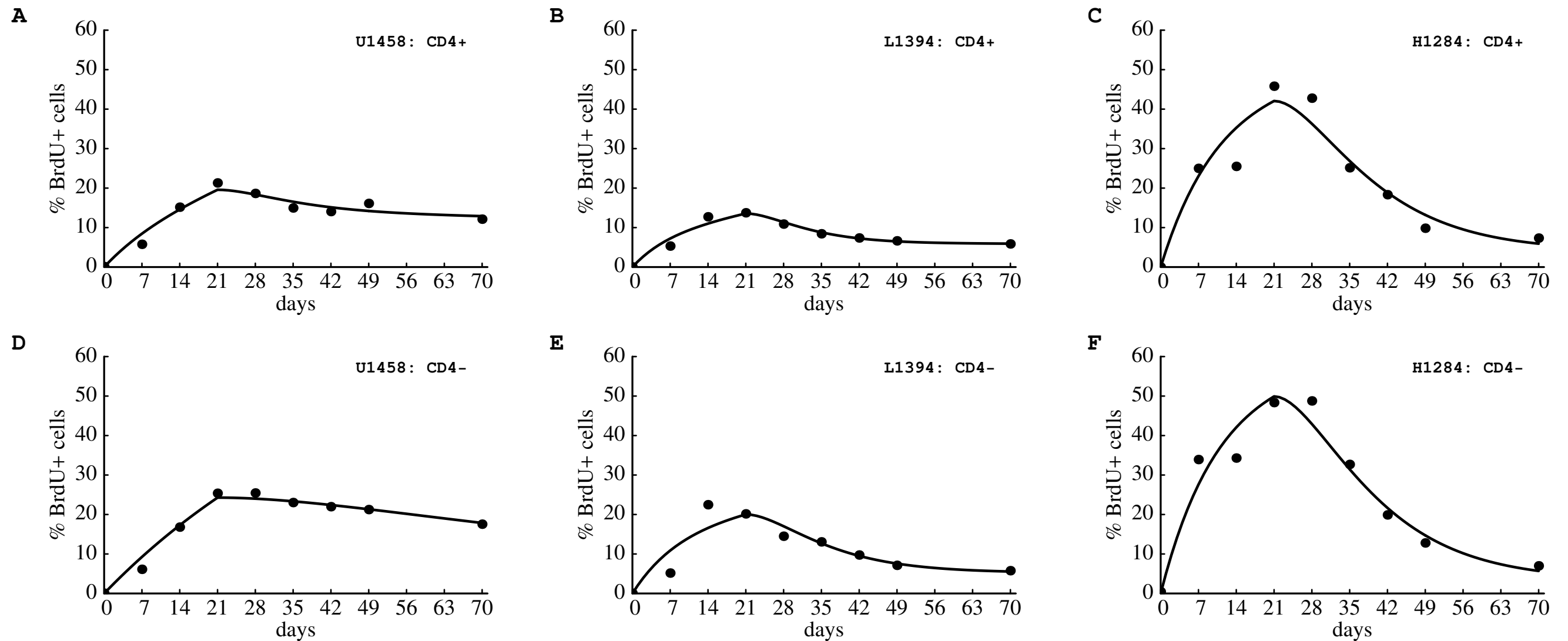
Model also allows one to define a
"mean fluorescence intensity" (MFI).

MFI need not decline much when
fraction of BrdU⁺ cells is decreasing

(Parretta: threshold 1θ at 0.25)

Adding on heterogeneity to the model

$$L(t) = \begin{cases} \sum_{i=1}^k \alpha_i \sum_{n=1}^{\infty} H(l_n - l_\theta) \times f_n(t, p_i), & \text{if } t \leq T, \\ \sum_{i=1}^k \alpha_i \sum_{n=1}^{\infty} \sum_{m=1}^{\infty} H(l_{n,m} - l_\theta) \times f_n(T, p_i) \times f_m(t - T, p_i), & \text{otherwise,} \end{cases} \quad \begin{array}{l} k \text{ times} \\ p_i = d_i \end{array}$$

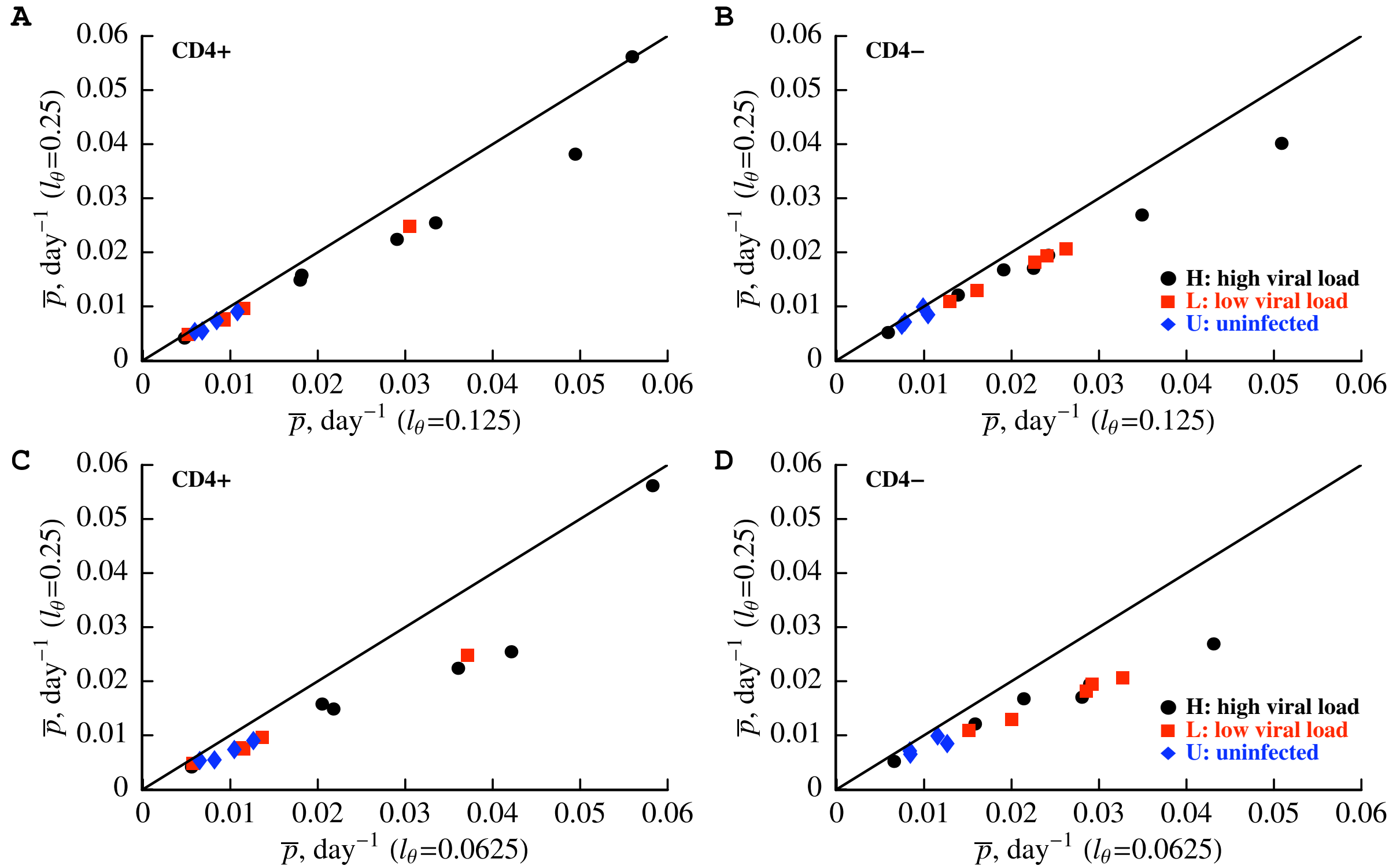


BrdU data from uninfected and SIV-infected monkeys.

We no longer need a large source.

Average turnover rate depends on the detection limit.

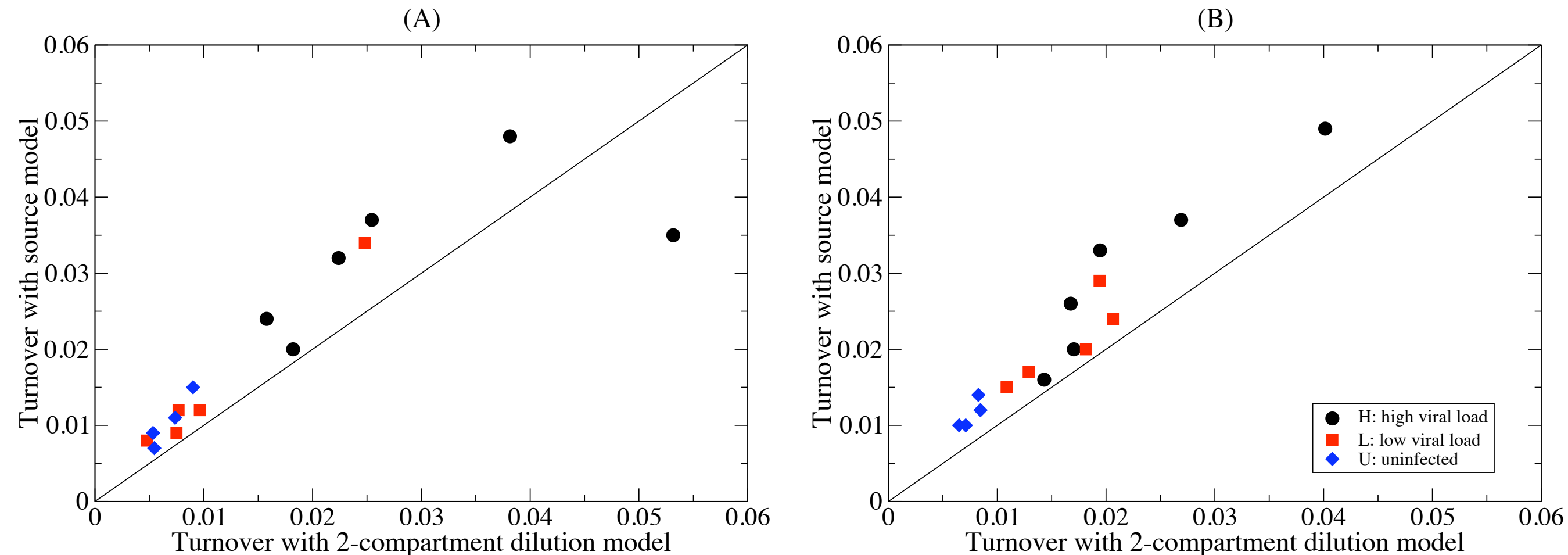
Estimated turnover decreases with detection limit



Threshold $l_{\theta} = 0.25$ fits best

but differences in quality of the fit are small

Dilution model estimates lower turnover rates



Small differences in quality of the fits

Threshold ι_θ at 0.25

Difference between BrdU and deuterium

BrdU:

$$\begin{aligned} dT_U/dt &= -(p + d)T_U, & dT_L/dt &= \sigma + 2pT_U + (p - d)T_L \text{ during labeling, and} \\ dT_U/dt &= \sigma + (p - d)T_U, & dT_L/dt &= (p - d)T_L \text{ during de-labeling.} \end{aligned}$$

Fraction labeled:

$$\frac{dL}{dt} = [2p + s(t)](1 - L) \quad \text{and} \quad \frac{dL}{dt} = -s(t)L \quad \text{where} \quad s(t) = \frac{\sigma}{T(t)},$$

At steady state:

$$dL/dt = (p + d)(1 - L) \quad \text{and} \quad dL/dt = (p - d)L$$

Renewing (s=0): $L' = 2p(1-L)$ but **Source (p=0):** $L' = d(1-L)$

Deuterium:

$$\begin{aligned} dT_U/dt &= -dT_U, & dT_L/dt &= \sigma + p[T_U + T_L] - dT_L \text{ during labeling, and} \\ dT_U/dt &= \sigma + p[T_U + T_L] - dT_U, & dT_L/dt &= -dT_L \text{ during de-labeling,} \end{aligned}$$

Fraction labeled:

$$\frac{dL}{dt} = [p + s(t)](1 - L) \quad \text{and} \quad \frac{dL}{dt} = -[p + s(t)]L \quad \text{where} \quad s(t) = \frac{\sigma}{T(t)},$$

At steady state:

$$dL/dt = d(1 - L) \quad \text{and} \quad dL/dt = -dL$$

Depends
on d only!

Conclusions on using labeling to infer T cell population dynamics

Interpretation of deuterium data seemed so simple: no toxic effects, no dilution, loss by death only. Nevertheless very contradictory estimates.

Important to gather dense data having several points during early up and down-slope and fit these with an appropriate model

Naive T cells have life spans of several years in humans and several weeks in mice. Memory T cells live shorter than naive T cells.

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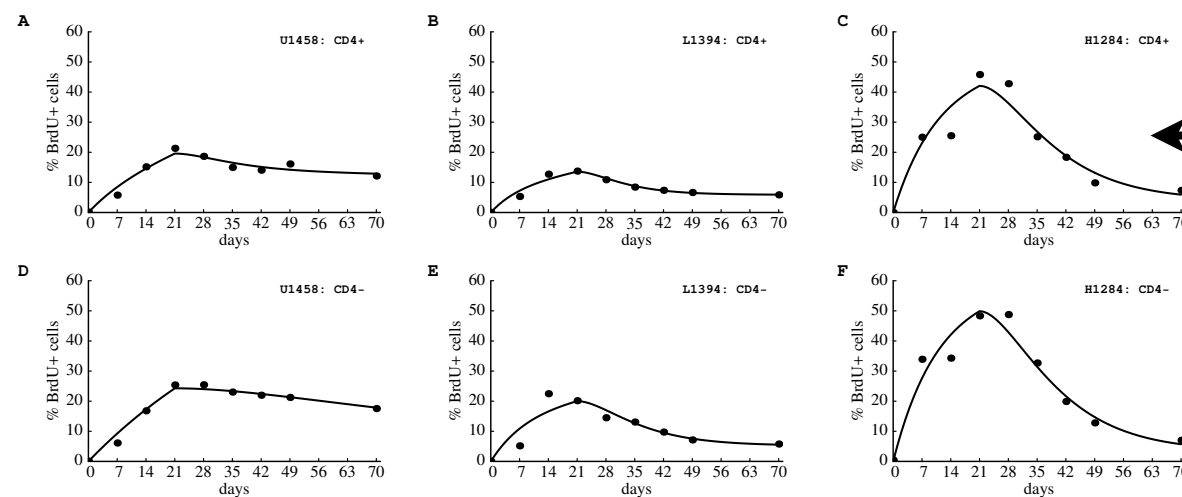
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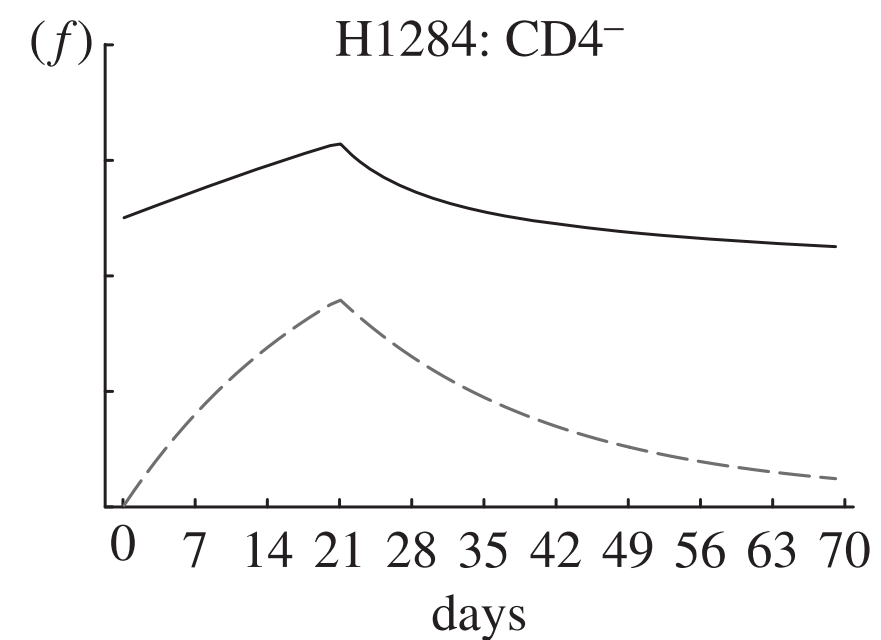
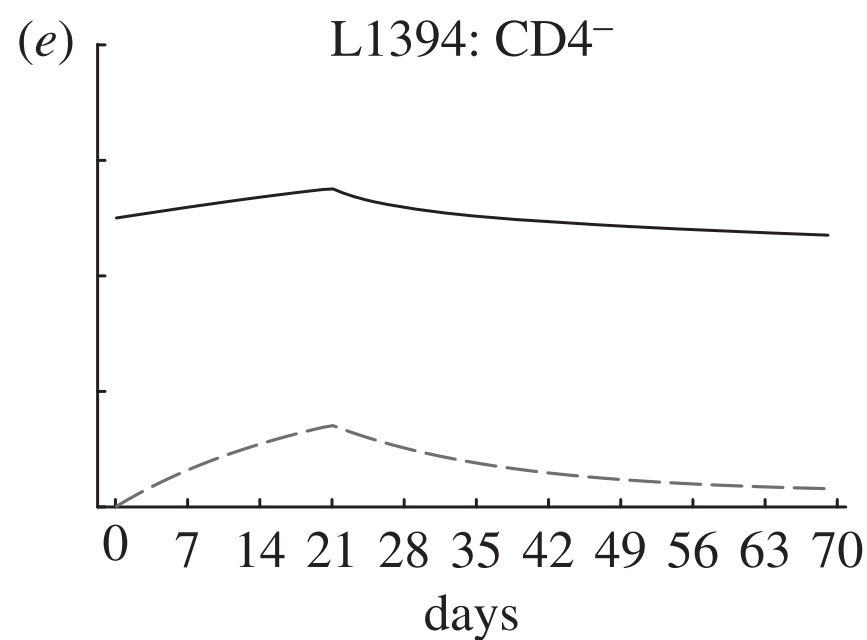
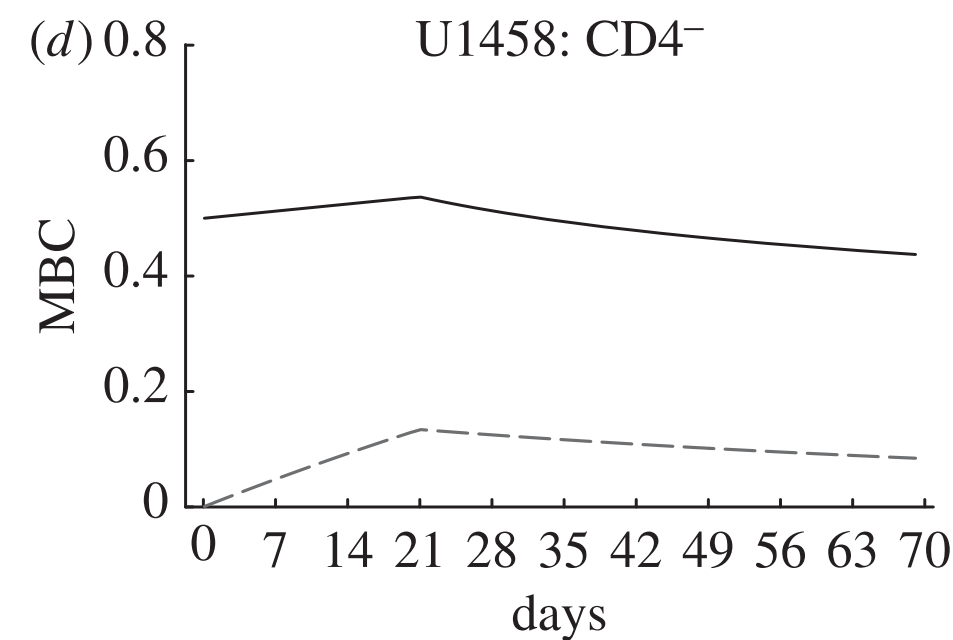
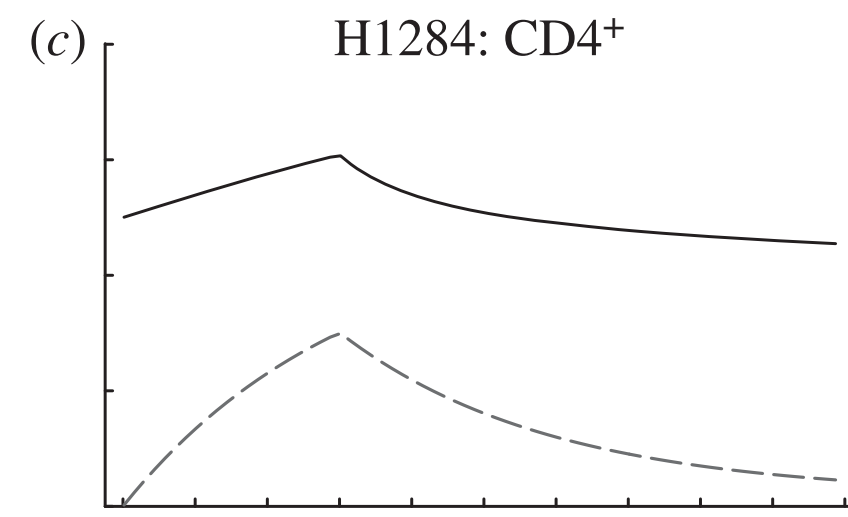
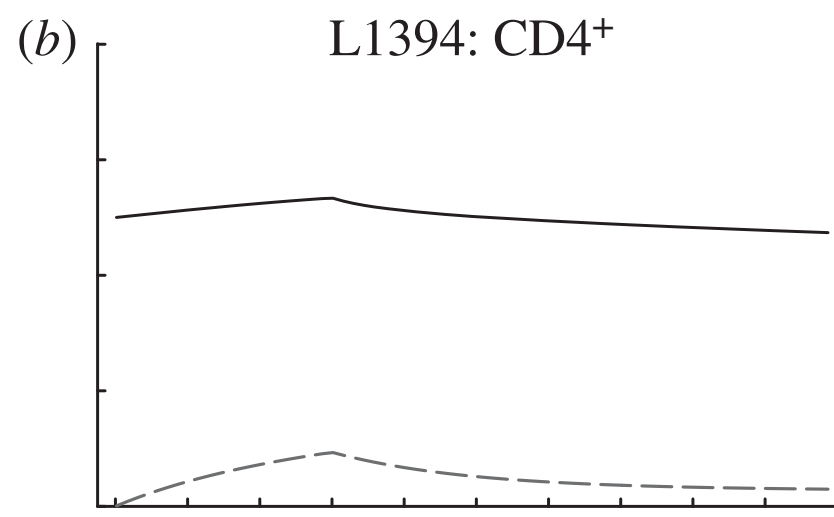
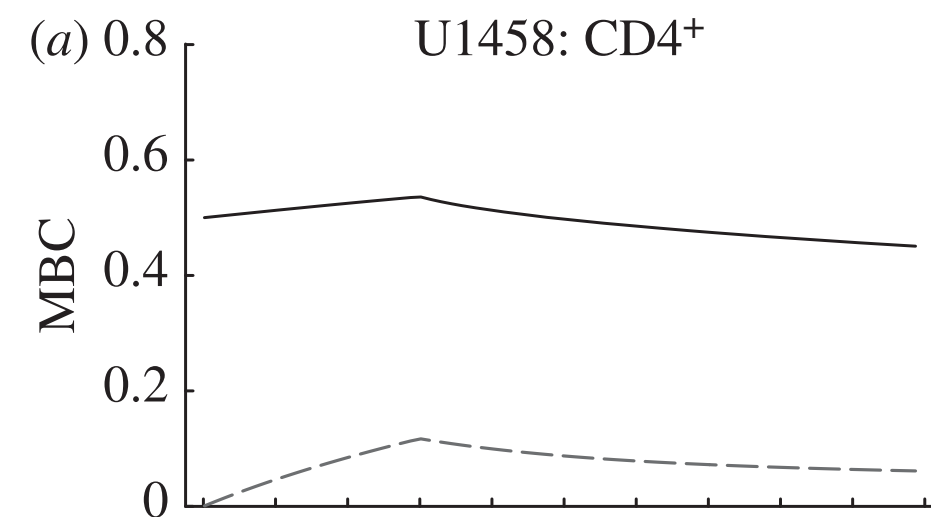
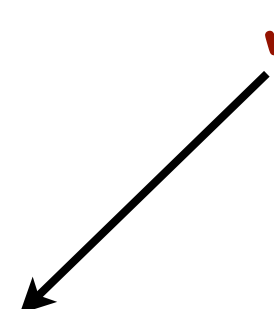
Alan Perelson

Adding on heterogeneity: MFI

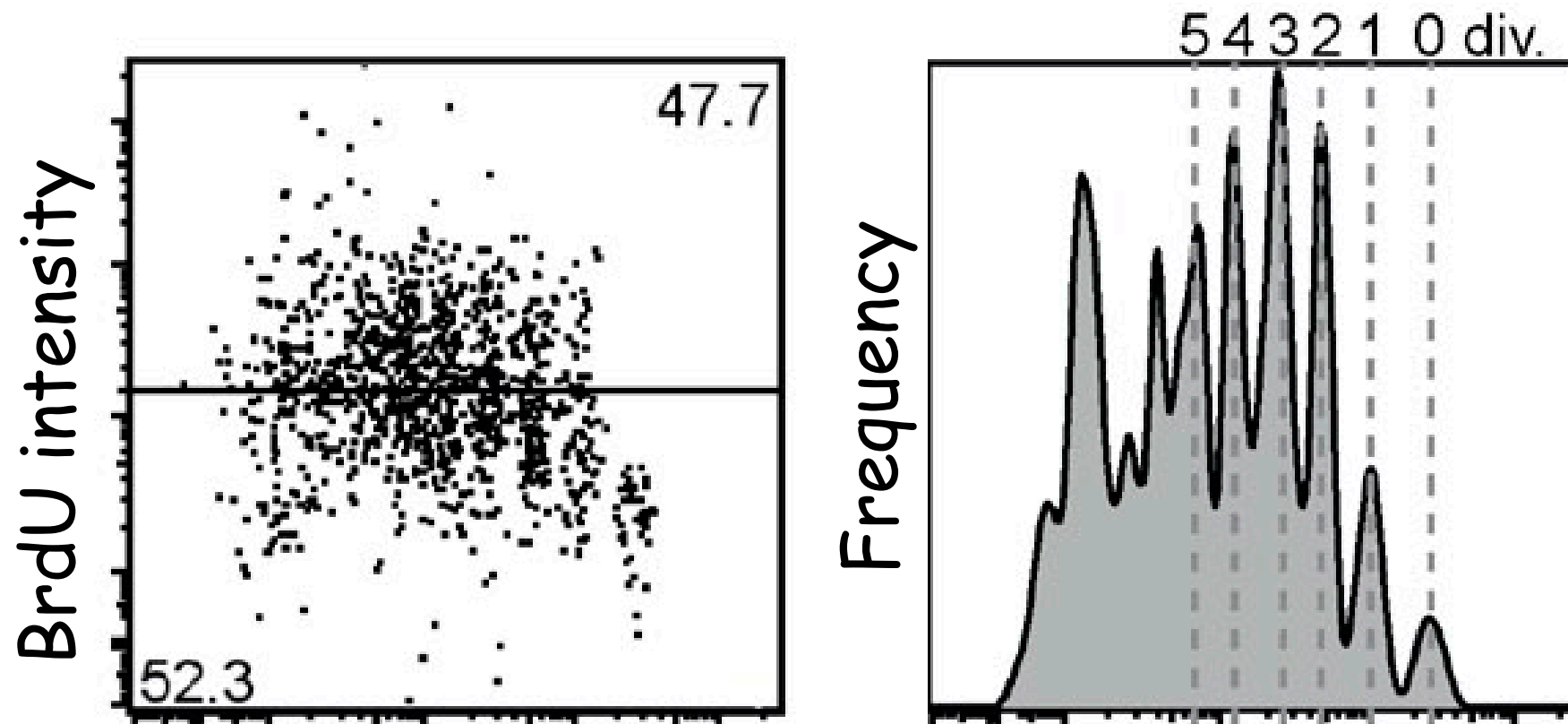


%BrdU⁺

"MFI"



Problem: is BrdU intensity reflecting #divisions?



CFSE intensity

From: Takizawa.jem11

In vivo CFSE labeled cells after 14d BrdU up-labeling

Intensity not linear in number of divisions

(we expect b , $b+1/2$, $b+3/4$, $b+7/8$, ...; scale is log)

Could help to explain absence of variation in BrdU intensity profiles and/or MFI