

# Supplementary Document for Pedersen et al. (2013)

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This document is the Supplementary Document for the manuscript entitled “A kinetic model explains why shorter and less affine enzyme-recruiting oligonucleotides can be more potent” and it is a vignette for the R-package ASOmodels.

With the aim of maximising reproducibility, the functions and data used to produce the figures in the main manuscript and this supplementary document are available after installing the ASOmodels package in R.

```
> require(devtools)
> install_github(ASOmodel, username=lykkep, build=FALSE)
> require(ASOmodels)
```

The ASOmodels package defines and documents the following functions that are used in this document:

Trel	TrelNO	Trelstoc
plot.doseresponse	EP	diffASO
EC50NO	EC50stoc	EC50

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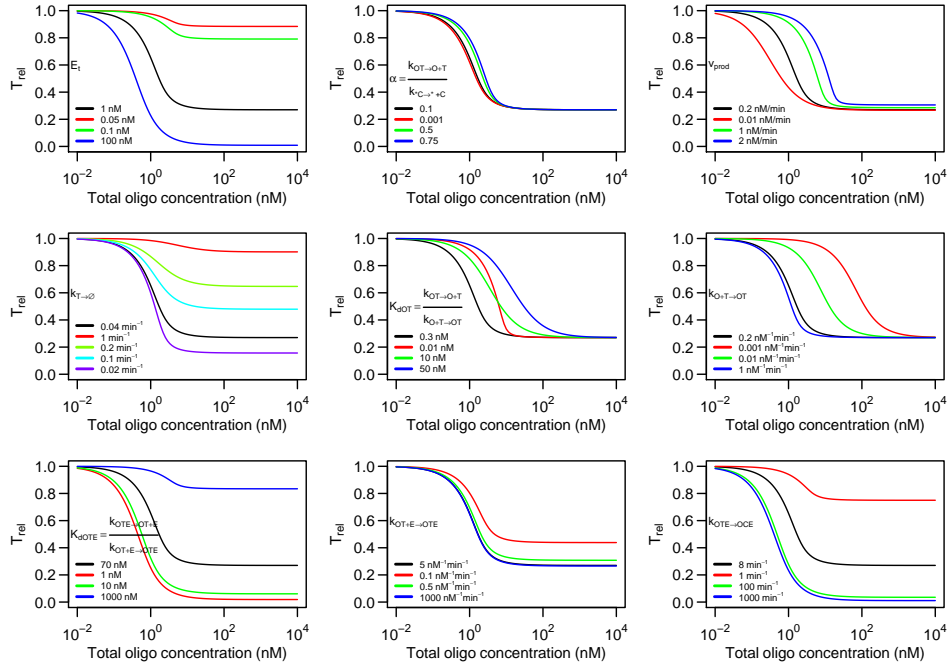
## Supplementary Figure S1

The R-function `Trel()` calculates  $T_{\text{rel}}$  as a function of  $O_t$  and the set of parameters as in the example below:

```
> #The parameters are in vector-format
> parms <- c(Et = 1, KdOT = 0.3, kOpT = 0.2, KdOTE = 70, kOTpE = 5,
+           vprod = 0.2, kdegrad = 0.04, alpha=0.1, kcleav = 8)
> Trel(Ot=1, param=parms)
```

```
[1] 0.6538694
```

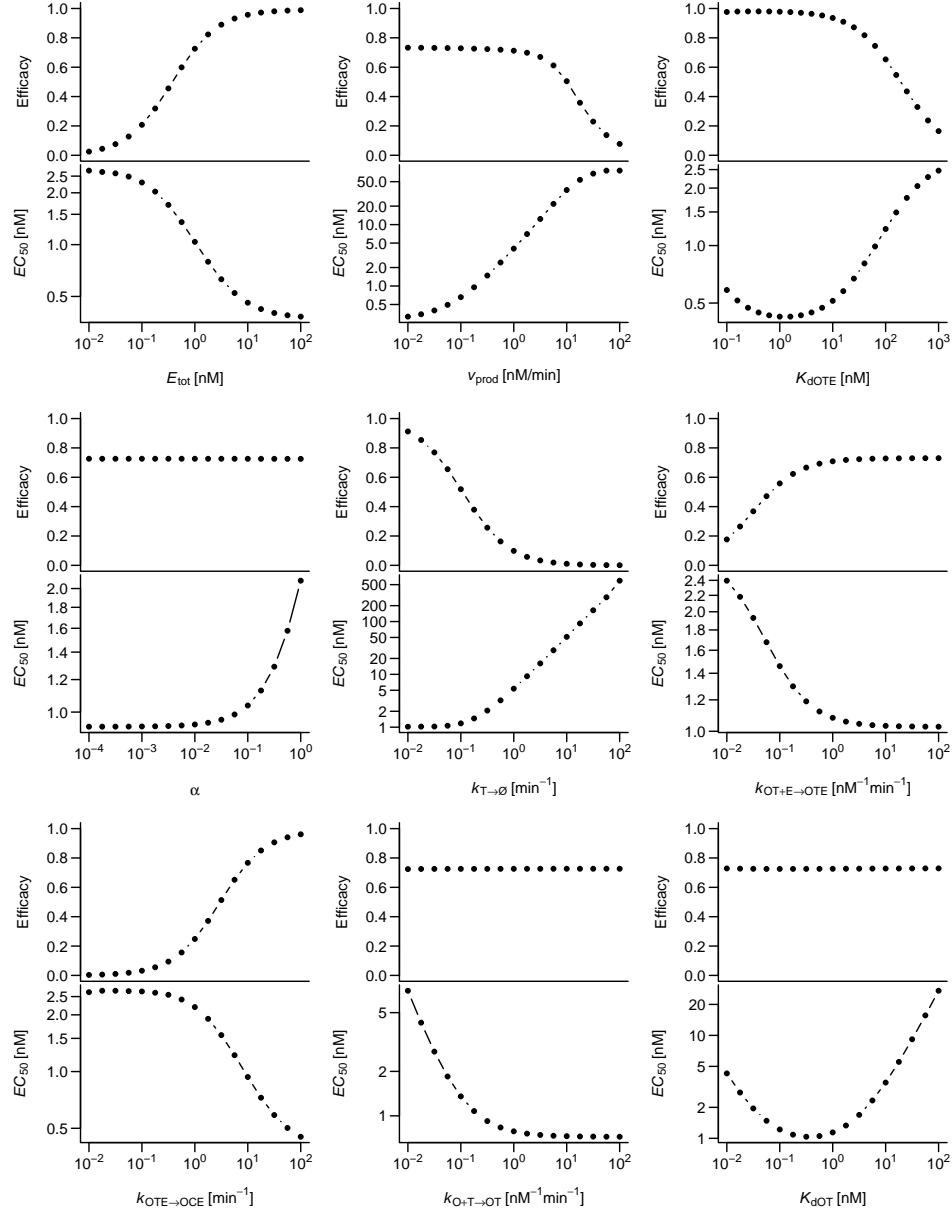
$T_{\text{rel}}$  can be calculated for a range of different oligonucleotide concentrations ( $O_t$ ) and from this a dose-response curve is obtained. Supplementary Figure S1 shows the change in the dose-reponse curves as the parameters vary. These plots are produced using `plot.doseresponse()`.



Supplementary Figure S1: Dose-response curves for different values of  $E_t$ ,  $\alpha$ ,  $v_{\text{prod}}$ ,  $k_{T \rightarrow \emptyset}$ ,  $K_{\text{dOT}}$ ,  $k_{\text{O}+\text{T} \rightarrow \text{OT}}$ ,  $K_{\text{dOTE}}$ ,  $k_{\text{OT}+\text{E} \rightarrow \text{OTE}}$ , and  $k_{\text{OTE} \rightarrow \text{OCE}}$  (top, left to bottom, right). Black lines correspond to the parameter values listed in Supplementary Table.

## Supplementary Figure S2

Using the R-function `drm()` from the `drc` package (v2.3-0) a dose-response curve is fitted to  $T_{\text{rel}}$  as a function of  $O_t$  to obtain an  $EC_{50}$ -value and the efficacy. It is observed that the potency and efficacy varies for varying parameter values as shown in Supp. Fig. S2.



Supplementary Figure S2: Efficacy and  $EC_{50}$  is plotted as functions of parameter values for  $E_{\text{tot}}$ ,  $K_{\text{dOTE}}$ ,  $v_{\text{prod}}$ ,  $\alpha$ ,  $k_{\text{O}+\text{T} \rightarrow \text{OT}}$ ,  $k_{\text{OT}+\text{E} \rightarrow \text{OTE}}$ ,  $k_{\text{T} \rightarrow \text{O}}$ ,  $k_{\text{OTE} \rightarrow \text{OCE}}$ .

## Supplementary Figure S3

The stochastic simulation of the model is carried out by use of the `ssa()` R-function from the GillespieSSA package (v.0.5-4). The inputs to `ssa` are an initial state vector (`x0`), which is the initial number of molecules, a propensity vector (`a`), which denotes the different states of the system, a state-change matrix (`nu`), which is the change in number of molecule (rows) if a reaction occur (column), the model-parameters (`parms`) and the final time (`tf`).

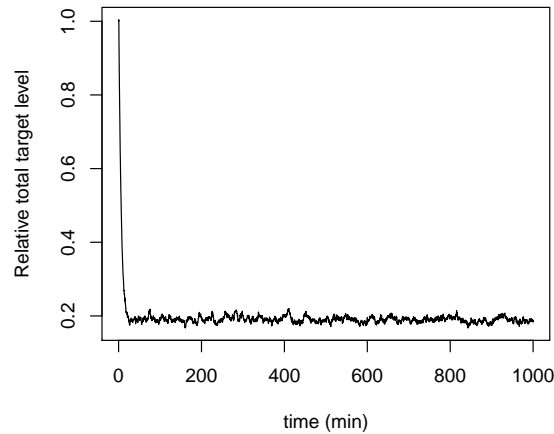
```
> library(GillespieSSA)
> #Model parameters
> parms1 <- c(kOpT = 2E-5, kOTpE = 50E-5, vprod = 150, kdegrad = 0.04,
+             kcleav = 2, kOT = 0.06, kOTE = 2, kC = 0.1)
> #Initital state vector
> x0 <- c(Tt = parms1["vprod"]/parms1["kdegrad"],
+         OT = 0, OTE = 0, E = 1e3, O = 1e5, OCE = 0, OC = 0)
> names(x0) <- c(Tt, OT, OTE, E, O, OCE, OC)
> #Propensity vector
> a <- c("vprod", "kOpT*O*Tt", "kdegrad*Tt", "kOT*OT", "kOTE*OTE", "kdegrad*OT",
+        "kOTpE*OT*E", "kdegrad*OTE", "kcleav*OTE", "kC*OC", "kOTE*OCE" )
> #State-change matrix
> nu <- matrix(0, 7, length(a))
> dimnames(nu) <- list(names(x0), a)
> #T
> nu[Tt, c(vprod, kOT*OT)] <- 1
> nu[Tt, c(kOpT*O*Tt, kdegrad*Tt)] <- -1
> #OT
> nu[OT, c(kOpT*O*Tt, kOTE*OTE)] <- 1
> nu[OT, c(kOT*OT, kOTpE*OT*E, kdegrad*OT)] <- -1
> #OTE
> nu[OTE, c(kOTpE*OT*E)] <- 1
> nu[OTE, c(kOTE*OTE, kdegrad*OTE, kcleav*OTE)] <- -1
> #E
> nu[E, c(kOTE*OTE, kdegrad*OTE, kOTE*OCE)] <- 1
> nu[E, c(kOTpE*OT*E)] <- -1
> #O
> nu[O, c(kOT*OT, kdegrad*OTE, kdegrad*OT, kC*OC)] <- 1
> nu[O, c(kOpT*O*Tt)] <- -1
> #OCE
> nu[OCE, c(kcleav*OTE)] <- 1
> nu[OCE, c(kOTE*OCE)] <- -1
> #OC
> nu[OC, c(kOTE*OCE)] <- 1
```

```

> nu[OC,c(kC*OC)] <- -1
> #The Gillespie simulation
> Gillespie <- ssa( x0=x0,a=a,nu=nu,
+               parms = parms1,tf=1E3,method = "ETL")

```

Supplementary Figure S3 shows  $T_{\text{rel}}$  from the Gillespie simulation.



Supplementary Figure S3: The time-trace for the relative total target level when the model is simulated stochastically.

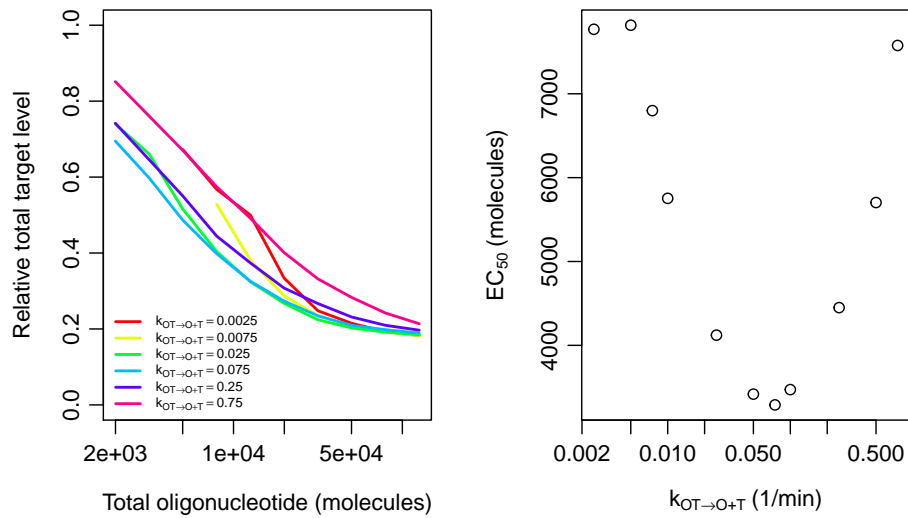
## Supplementary Figure S4

After a while the stochastic simulation reaches a plateau. In Supplementary Figure S3 the plateau starts around 50min. The mean of  $T_{\text{rel}}$  within the plateau is calculated through the R-function `Trelstoc()`. Using this function we can generate dose-response curves (Supplementary Figure S4, left). From these  $EC_{50}$ -values can be calculated using `EC50stoc()` and they are subsequently plotted as a function of  $k_{OT \rightarrow O+T}$  (Supplementary Figure S4, right). Note that as in the deterministic case (see main manuscript) an optimal affinity is observed.

```

> ##### Sequence of k(OT -> O+T) values
> lseq <- c(1,2.5,5,7.5)
> lKOT <- c(1E-3*lseq[-1],1E-2*lseq,1E-1*lseq)
> ##### Generation of dose-response curves
> DRcurve <- lapply(lKOT,function(ki){
+               sapply(10^seq(2.5,6,by=0.2),
+               function(i) Trelstoc(i,kOT=ki)$Tstat))})
> DRc <- lapply(DRcurve,function(x) x[,!is.na(x[3,])])
> ##### Calculation of EC50
> EC50_lKOT <- sapply(1:length(DRc),
+               function(x){EC50stoc(DRc[[x]][2,],DRc[[x]][1,])})

```



Supplementary Figure S4: Left: Dose-response curves for various values of  $k_{OT \rightarrow O+T}$  (compare to Supplementary Figure S1,middle). Right:  $EC_{50}$  as a function of  $k_{OT \rightarrow O+T}$ . A high value of  $k_{OT \rightarrow O+T}$  corresponds to a low affinity.

## Supplementary Figure S5

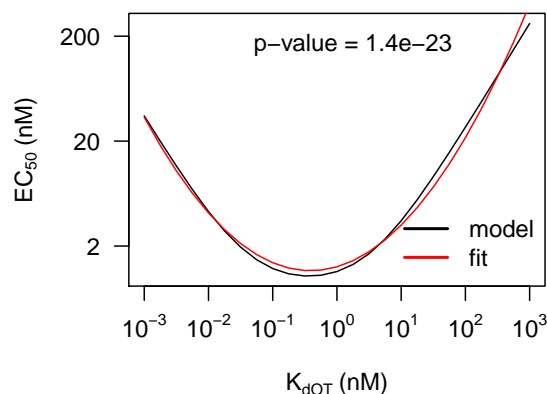
We are interested in  $EC_{50}$  as a function of  $K_{dOT}$ . This is calculated through the ASOmodel-function `EC50()` that takes  $K_{dOT}$  and the set of parameters as input:

```
> EC50(KdOT=0.1,param=parms)
```

```
EC50
1.219307
```

For a range of  $K_{dOT}$ -values, the corresponding  $EC_{50}$ -values can be calculated. These can be fitted to a parabola using the R-function `lm()`, see Supplementary Figure S2.

```
> D1_seq <- 10^seq(-3,3.2,by=0.25)
> ECseq <- sapply(D1_seq,EC50)
> FitPar <- lm(log10(ECseq) ~ log10(D1_seq) + I(log10(D1_seq)^2))
```



Supplementary Figure S5:  $EC_{50}$  as a function of  $K_{dOT}$  is fitted on a log-log scale to a parabola.

## References

- [1] M. Frieden, S. M. Christensen, N. D. Mikkelsen, C. Rosenbohm, C. A. Thru, M. Westergaard, H. F. Hansen, H. Ørum, and T. Koch. Expanding the design horizon of antisense oligonucleotides with alpha-L-LNA. *Nucleic Acids Res.*, 31(21):6365–6372, 2003.
- [2] G. M. Hashem, L. Pham, M. R. Vaughan, and D. M. Gray. Hybrid oligomer duplexes formed with phosphorothioate DNAs: CD spectra and melting temperatures of S-DNA.RNA hybrids are sequence-dependent but consistent with similar heteronomous conformations. *Biochemistry*, 37(1):61–72, Jan. 1998.
- [3] R. Stanton, S. Sciabola, C. Salatto, Y. Weng, D. Moshinsky, J. Little, E. Walters, J. Kreeger, D. Dimattia, T. Chen, T. Clark, M. Liu, J. Qian, M. Roy, and R. Dullea. Chemical Modification Study of Antisense Gapmers. *Nucleic Acid Ther*, 22(5):344–359, Aug. 2012.