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## 1 Title

2 In vitro transcription accurately predicts lac repressor phenotype in vivo in Escherichia coli

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Abstract

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12 A multitude of studies have looked at the *in vivo* and *in vitro* behavior of the lac repressor 13 binding to DNA and effector molecules in order to study transcriptional repression, however 14 these studies are not always reconcilable. Here we use in vitro transcription to directly mimic the 15 *in vivo* system in order to build a self consistent set of experiments to directly compare *in vivo* 16 and *in vitro* genetic repression. A thermodynamic model of the lac repressor binding to operator 17 DNA and effector is used to link DNA occupancy to either normalized in vitro mRNA product or 18 normalized *in vivo* fluorescence of a regulated gene, YFP. An accurate measurement of repressor, 19 DNA and effector concentrations were made both *in vivo* and *in vitro* allowing for direct 20 modeling of the entire thermodynamic equilibrium. In vivo repression profiles are accurately 21 predicted from the given *in vitro* parameters when molecular crowding is considered. 22 Interestingly, our measured repressor-operator DNA affinity differs significantly from previous 23 *in vitro* measurements. The literature values are unable to replicate *in vivo* binding data. We 24 therefore conclude that the repressor-DNA affinity is much weaker than previously thought. This 25 finding would suggest that *in vitro* techniques that are specifically designed to mimic the *in vivo* 26 process may be necessary to replicate the native system.

### 13 Introduction

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The lac genetic switch consists of the lac repressor, a short "operator" DNA sequence,
and effector molecules (Swint-Kruse & Matthews, 2009). The minimal functional lac repressor is
homo-dimeric and includes an N-terminal DNA binding domain and two effector binding sites
(one per monomer). Repressor binds to operator DNA preventing RNA polymerase from
transcribing downstream genes. Effector molecules bind to each effector binding site causing an
allosteric transition wherein repressor dissociates from operator DNA allowing transcription to
proceed (Lewis, 2005). Previously our lab has used a standard Monod, Wyman, and Changeux
(MWC) model of thermodynamic equilibrium to model the behavior of the lac genetic switch
(Fig. 1) (Monod, Wyman, & Changeux, 1965).

While the underpinnings of the lac genetic switch have been well characterized, it is less well understood how to utilize this information to achieve practical goals. How do we reduce the background leakiness of the repressor? Can you do so without compromising maximal inducibility? Can you target certain phenotypic properties through directed mutation? Will novel genetic switches developed in *E. coli* perform the same in different cell types? Significant advancement has been made in recent years towards answering these more complex questions.

30 Daber, et al. examined the number of effector molecules necessary to induce transcription 31 (Daber, Sharp, & Lewis, 2009). Hetero-dimeric lac repressors were created that bound either 0, 1 32 or 2 effector molecules and the *in vivo* regulation of a fluorescent gene was measured. An 33 analytical solution of a simplified MWC equilibria allowed for direct measurements of 34 dimensionless bulk parameters comprised of combinations of thermodynamic binding constants 35 and species concentrations. While these parameters were useful in showing that two effector 36 molecules are required for fully inducing the genetic switch, they were unable to measure the 37 thermodynamic constants themselves.

38 Daber, et al. next sought to link distinct perturbations of the lac genetic switch to changes 39 in thermodynamic parameters (Daber, Sochor, & Lewis, 2011). Mutations were made in the 40 DNA binding domain and effector binding pocket of the repressor. They were able to measure 41 the repressor-effector binding affinities; however they still could only measure a dimensionless 42 constant which contained repressor concentration and repressor-DNA affinity. Mutations in the 43 DNA binding domain of the lac repressor were linked to changes in the repressor-DNA affinity. 44 Alternatively, changes in the repressor concentration could also account for the phenotype. 45 Mutations in the effector binding domain did alter the effector binding affinities. Interestingly, 46 effector binding domain mutations were also linked to changes in the conformational equilibrium 47 of the repressor, but once again changes in the repressor concentration could account for the 48 phenotype. These results were encouraging evidence that directed mutations lead to directed 49 phenotypes, but the question of repressor concentration clouded the picture.

A study by Poelwijk, et al. looked for unique phenotypes through random mutagenesis of
the lac repressor (Poelwijk, de Vos, & Tans, 2011). Mutants were identified which exhibited an
inverted repression behavior; a phenotype also found by Daber, et al. by mutating the effector
binding domain (Daber, Sochor, & Lewis, 2011). Interestingly, Poelwijk's mutations were in

regions physically distinct from either the DNA or effector binding domains. One potential

55 explanation is that the mutations destabilize the folded form of the repressor, altering the

56 conformational landscape. Mutagenesis of the repressor can result in more than just predictable

57 changes of thermodynamic binding constants.

58 Central to all of these studies is the use of *in vivo* data to understand the behavior of 59 genetic switches. It has been pointed out that a lack of corroborating *in vitro* evidence prevents 60 the identification of other processes which may significantly play into the equilibrium, such as 61 non-specific DNA binding or effector uptake (Tungtur et al., 2011). They attempted to measure 62 the thermodynamic binding of a LacI/GalR hybrid repressor both *in vitro* and *in vivo*. Notably, a 63 DNA pull down assay was used to quantify the *in vivo* concentration of their hybrid repressor. 64 Unfortunately, they were unable to rectify a greater than 25-fold difference between their two 65 data sets. This indicates that they are missing a significant contributor to the genetic switch by 66 only analyzing in vivo data.

Here we sought to overcome the limitations of past studies three ways: 1.) measure the *in vivo* concentration of the lac repressor, 2.) measure the *in vitro* transcription of purified lac genetic switch, and 3.) use an assumption free solution to the MWC equilibrium to model both *in vitro* and *in vivo* data.

We were able to measure lac repressor concentration *in vivo* and use *in vitro* transcription to assess the purified lac genetic switch. Furthermore, we found excellent agreement between *in vitro* and *in vivo* data when molecular crowding was taken into consideration. We do however find that the repressor-DNA affinity is much lower than has previously been measured *in vitro*. Additional concerns, such as effector uptake and non-specific DNA binding do not appear to play significant roles.

# 77 Materials and methods

# 78 In vivo measurement of lac genetic switch

Reporter plasmid was made as previously reported (Daber & Lewis, 2009) with the O1
operator sequence (5'-AA TT GTG AGC G GAT AAC AA TT-3') followed by YFP and
providing ampicillin (AMP) resistance. Lac repressor was expressed on a second plasmid as
previously described (Daber & Lewis, 2009) providing chloramphenicol (CAM) resistance. A Cterminal mCherry tag was added to the Lac repressor gene after an 11bp linker to create the LacmCherry construct.

85 We double transformed reporter and repressor plasmids into EPB229 cells ( $F^-\Delta(lacI-$ 

86 lacA)::frt). These cells were derived from the MG1655 "wild type" line. Colonies were picked in

87 triplicate into MOPS minimal media with 0.4% glucose, AMP and CAM and grown overnight at

88 37C with shaking.  $50\mu$ L of the overnight culture was used to inoculate 1mL fresh MOPS

- 89 minimal media supplanted with varying amounts of IPTG. We measured optical density at
- 600nm (OD<sub>600</sub>), YFP fluorescence (excite: 510 nm emit: 535 nm), and mCherry fluorescence
  (excite: 585 nm emit: 610 nm) for all wells at 1 hour intervals over a 12 hour period using a
- 92 TECAN M1000 plate reader in 384 well optical bottom plates (Corning).
- **93** *Purification of Lac-mCherry*

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94 Lac-mCherry was cloned into the pBAD-DEST49 expression vector (Clontech). A 6xHis 95 C-terminal tag was added to aid in purification. BL21(DE3) cells were transformed and grown to 96 mid-log at 37C with shaking in 2xYT media. At mid-log growth, expression of Lac-mCherry was 97 induced with the addition of arabinose 0.1% (v/v) and the temperature was reduced to 15C and 98 cells were allowed to grow overnight (approximately 12-16 hours). Cell extract was purified with 99 Ni-NTA beads (Clontech) and a sizing column (HiLoad 16/60 Superdex 75 Prep Grade with 100 AKTA Prime FPLC) and purified Lac-mCherry was equilibrated into GF buffer (200 mM Tris 101 pH 7.4, 200 mM KCl, 10mM EDTA, 3mM DTT).

#### 102 Measuring in vivo concentrations of the lac repressor

EPB229 cells were co-transformed with Lac-mCherry and O1 YFP reporter. An individual colony was picked into MOPS minimal media with 0.4% glucose, AMP and CAM and grown overnight at 37C with shaking. 50  $\mu$ L was innoculated into 1 mL fresh media and grown to mid-log phase.

Purified Lac-mCherry was quantitated with both a BCA Assay Kit (Pierce) and optical  $A_{280}$  measurements using a NanoDrop 2000 Spectrometer (Thermo Scientific). Dilutions were made over 8 orders of magnitude and 50 µL was loaded into clear bottom 384 well plates in triplicate. mCherry fluorescent measurements (excite: 585 nm emit: 610 nm) were made using various gains to establish linear regimes for the instrument (TECAN M1000).

We established a raw cell count by plating dilutions of a culture of EPB229 cells. Serial dilutions were made over 10 orders of magnitude and each dilution had  $OD_{600}$  measured (TECAN M1000 and Ultrospec 2100 pro) and 100 µL plated onto LB agar with AMP and CAM. We found  $1.92x10^6$  cells/µL at mid-log growth phase which is about two-fold higher than standard estimates of  $1x10^6$  cells/µL for *E. coli*. Aliquots of known cell counts were then used to establish a linear relationship with  $OD_{600}$  on our plate reader. Similarly, purified Lac-mCherry of known concentration was used to establish a linear relationship with mCherry fluorescence on our plate reader at a fixed gain.

120 EPB229 cells were co-transformed with plasmid constitutively expressing Lac-mCherry 121 and a reporter plasmid which has YFP under the control of the natural operator O1. We measured 122 mCherry fluorescence at a fixed gain and  $OD_{600}$  from which we calculated the concentration of 123 Lac-mCherry in the well and the number of cells in the well. The approximate volume of *E. coli* 124 was estimated to be  $1 \times 10^{-15}$  L (Kubitschek & Friske, 1986). Multiplying volume of *E. coli* by 125 number of cells allows us to estimate what fraction of the well volume is intracellular.

Calibration of raw mCherry fluorescent signal and OD<sub>600</sub> was converted to intracellular
 repressor concentration.

128 Fluorescent data processing

129 In vivo data was normalized for growth by measuring cells in triplicate as they were 130 growing. All data points collected were then fit to a  $2^{nd}$  order polynomial to obtain a curve which

is fluorescence as a function of OD<sub>600</sub>. Positive control was established by co-transforming

132 EPB229 cells with O1 YFP reporter and a CAM plasmid without Lac-mCherry (pABD34). YFP

133 signal was normalized to the polynomial fit from the positive control. Final values for fitting

134 were calculated for cells at approximately mid-log growth phase ( $OD_{600} = 0.4$ ).

#### 135 *Measuring* in vitro transcription

A reporter plasmid was made with the O1 operator after a T7 promoter. Reporter waslinearized to 450bp and purified by spin column purification (Clontech).

138 MaxiScript T7 kit (Ambion) was used to perform *in vitro* transcription.  $CTP[\alpha^{-32}P]$  was 139 incorporated into mRNA transcripts and the water fraction of the standard reaction was 140 supplanted with varying concentrations of Lac-mCherry and IPTG. Transcription was allowed to 141 proceed for 30 minutes at 37C until halted by boiling. Samples were loaded onto polyacrylamide 142 gels and electrophoresis was used to separate free  $CTP[\alpha^{-32}P]$  from that incorporated into 143 mRNA. Gels were dried and exposed to radiological plates. Plates were imaged on a Typhoon 144 scanner and bands were quantitated using ImageJ (NIH).

#### 5 Modeling

Experimentally, we would like to measure the output from a promoter regulated by the lac genetic switch. It is assumed that transcription by RNA polymerase from the promoter is linearly related to the occupancy of the DNA operator within the promoter by the lac repressor,

transcription 
$$\propto \frac{[O]}{[O]_{tot}}$$
 (1)

In order to model experimental data, we need to compute the occupancy of the DNA operator in terms of the thermodynamic constants ( $K_{RR*}$ ,  $K_{RE}$ ,  $K_{R*E}$ ,  $K_{RO}$ , and  $K_{R*O}$ ) and the total concentration of repressor, effector and operator ( $[R]_{tot}$ ,  $[E]_{tot}$ , and  $[O]_{tot}$ ).

2. Start by defining the following affinity constants in equilibrium:

$$K_{RR*} = \frac{[R*]}{[R]}$$
(2)

$$K_{RE} = \frac{[RE]}{[R][E]}$$
(3)

$$K_{[R^*E]} = \frac{[R^*E]}{[R][E]}$$
(4)

$$K_{\rm RO} = \frac{[\rm RO]}{[\rm R][\rm O]}$$
(5)

$$K_{R^{*O}} = \frac{\lfloor R^{*O} \rfloor}{\lfloor R^{*} \rfloor [O]}$$
(6)

We also need to define the total concentrations of operator, effector and repressor in terms of the individual bound and conformational states,

$$[O]_{tot} = [O] + [RO] + 2[REO] + [RE_2O] + [R*O] + 2[R*EO] + [R*E_2O]$$
(7)

$$[E]_{tot} = [E] + 2[RE] + 2[RE_2] + 2[R^*E] + 2[R^*E_2] + 2[ROE] + 2[ROE_2] + 2[R^*OE] + 2[R^*OE_2]$$
(8)

$$[R]_{tot} = [R] + 2[RE] + [RE_2] + [R^*] + 2[R^*E] + [R^*E_2] + [RO] + 2[REO] + [RE_2O] + [R^*O] + 2[R^*EO] + [R^*E_2O]$$
(9)

Of note are the various coefficients of 2. All of the singly bound effector species are degenerate since the effector can bind to either the left or right effector site, which gives rise to the statistical mass balancer 2. For Equation 8, the doubly bound effector species have two effector molecules bound and hence are doubled.

The strategy is to write all of the equations in terms of the free species concentrations ([R], [E], [O]) and the equilibrium constants in Equations 2-6. Then we try to rearrange such that we can make polynomials of just [E]. The reasons will become apparent after we have done the above operations.

163 Starting with Equation 9, we re-write using only free species and constants,

164

$$[RO] = K_{RO}[R][O]$$
<sup>(10)</sup>

$$[\text{REO}] = K_{\text{RE}} K_{\text{RO}}[\text{R}][\text{E}][\text{O}]$$
(11)

$$[RE_2O] = K_{RE}^2 K_{RO}[R][E]^2[O]$$
(12)

$$[R*O] = K_{RR*} K_{R*O}[R][O]$$
(13)

$$[R*EO] = K_{RR*} K_{R*E} K_{R*O}[R][E][O]$$
(14)

$$[R*E_2O] = K_{RR*}K_{R*E}^2 K_{R*O}[R][E]^2[O]$$
(15)

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$$[R]_{tot} = [R] + 2[R][E]K_{RE} + [R][E]^{2}K_{RE}^{2} + [R]K_{RR*} + 2[R][E]K_{RR*}K_{R*E} + [R][E]^{2}K_{RR*}K_{R*E}^{2} + [R][O]K_{RO} + 2[R][O][E]K_{RO}K_{RE} + [R][O][E]^{2}K_{RO}K_{RE}^{2} + [R][O]K_{RR*}K_{R*O} + 2[R][O][E]K_{RR*}K_{R*O}K_{R*E} + [R][O][E]^{2}K_{RR*}K_{R*O}K_{R*E}^{2}$$
(16)

We then make the following definitions,

$$\alpha_1 = 1 + K_{RR*} \tag{17}$$

$$\beta_1 = 2K_{RE} + 2K_{RR*}K_{R*E} \tag{18}$$

$$\gamma_1 = K_{RE}^2 + K_{RR*} K_{R*E}^2$$
(19)

$$\gamma_2 = 2K_{\rm RO} K_{\rm RE} \tag{20}$$

$$\delta_1 = K_{RO} K_{RE}^2 \tag{21}$$

$$\beta_2 = K_{RR^*} K_{R^{*O}} \tag{22}$$

$$\gamma_{3} = 2K_{RR^{*}}K_{R^{*0}}K_{R^{*E}}$$
(23)

$$\delta_2 = \mathbf{K}_{\mathrm{RR}^*} \mathbf{K}_{\mathrm{R}^{*\mathrm{O}}} \mathbf{K}_{\mathrm{R}^{*\mathrm{E}}}^2 \tag{24}$$

166

Substituting into Equation 16 and re-arranging to isolate [R],

$$[R] = \frac{[R]_{tot}}{\alpha_1 + [E]\beta_1 + [E]^2 \gamma_1 + [O](K_{RO} + [E]\gamma_2 + [E]^2 \delta_1 + \beta_2 + [E]\gamma_3 + [E]^2 \delta_2)}$$
(25)

167 The equation has been organized such that polynomials in [E] are apparent. As long as
168 we only add and multiply polynomials, they can trivially be treated as symbolic functions for
169 further simplification. We define the following polynomials,

$$\mathbf{B}_1 = \alpha_1 + [\mathbf{E}]\beta_1 + [\mathbf{E}]^2 \gamma_1 \tag{26}$$

$$B_2 = K_{RO} + \beta_2 + [E](\gamma_2 + \gamma_3) + [E]^2(\delta_1 + \delta_2)$$
(27)

Now substituting back into Equation 25,

$$[\mathbf{R}] = \frac{[\mathbf{R}]_{\text{tot}}}{\mathbf{B}_1 + [\mathbf{O}]\mathbf{B}_2}$$
(28)

We next want to follow the same path for [E] and [O]. Inspection of Equations 7-9 showthat we have already done the most complicated case. We can then quickly arrive at,

$$[O] = \frac{[O]_{tot}}{1 + [R]B_2}$$
(29)

The effector equation is similar, but it has a few extra coefficients of two within itsequations. We define two more polynomials,

$$A_1 = \beta_1 + 2[E]\gamma_1 \tag{30}$$

$$A_2 = \gamma_2 + \gamma_3 + 2[E](\delta_1 + \delta_2)$$
(31)

**175** Substituting into Equation 8,

$$[E]_{tot} = [E] + [R][E]A_1 + [R][E][O]A_3$$
(32)

176 We can then eliminate [O] by substituting Equation 29 into Equations 28 and 32. Since 177 we can only multiply and add polynomials, we multiply the denominator of Equation 29 on both 178 sides. Substituting into Equation 28,

$$[R]_{tot} + [R]B_2[R]_{tot} = [R]B_1 + [R]^2B_1B_2 + [R]B_2[O]_{tot}$$
(33)

Study 179 180 We then define the following polynomials,  $\varphi_1 = B_1 B_2$  $\varphi_2 = B_1 + B_2 ([O]_{tot} - [R]_{tot})$ Substituting into Equation 33,  $[R]^{2} \varphi_{1} + [R] \varphi_{2} = [R]_{tot}$ 181 The substitution of Equation 29 into Equation 32 requires the following definitions,

$$\psi_1 = [E] A_1 B_2 \tag{37}$$

(34)

(35)

(36)

$$\psi_2 = [\mathbf{E}](\mathbf{B}_2 + \mathbf{A}_1 + \mathbf{A}_2[\mathbf{O}]_{\text{tot}}) - \mathbf{B}_2[\mathbf{E}]_{\text{tot}}$$
(38)

182 We then arrive at,

$$[R]^{2}\psi_{1} + [R]\psi_{2} = [E]_{tot} - [E]$$
(39)

183 We now have two equations (Eqn. 36 and 39) with two unknowns ([R] and [E]). In 184 principal we can get this down to a single equation, but in order to do so the final polynomial becomes of a much higher order which prevents accurate computational solutions. 185

186 The strategy is then to guess at the free effector concentration to calculate Equations 34, 35, 37, and 38. Equations 36 and 39 can then be solved for [R] by looking for the roots to the 187 equation. When the correct free effector concentration ([E])is found the roots of Equation 36 and 188

- 189 Equation 39 will converge. By minimizing the difference between the roots a solution can be
- 190 reached. All other concentrations are then trivial to calculate once [R] and [E] are known.
- 191 Custom Matlab (Mathworks) software was written to numerically solve the MWC equilibria
- **192** (Matlab File Exchange ID #40602).

The accuracy of the solution is easily checked by using the bound and free species
concentrations to calculate the total species concentrations and thermodynamic parameters.
Calculated values should agree with input values.

Five independent thermodynamic parameters (K<sub>RE</sub>, K<sub>R\*E</sub>, K<sub>RO</sub>, K<sub>R\*O</sub>, and K<sub>RR\*</sub>) were used
for each model and all data points were simultaneously fit using a standard non-linear least
squares algorithm in Matlab.

A Monte Carlo approach was used to estimate error in the fit parameters. The known error of the experiment was used to generate data sets with random error. 100 such data sets were generated and a non-linear least squares fitting algorithm was used to fit the thermodynamic parameters. Standard deviation of these fit thermodynamic parameters was used as the error of the best fit for the actual data set.

# Results and Discussion

# Measuring the In Vivo Concentration of the Lac Repressor

We sought a method where we could simultaneously measure lac repressor concentration and transcriptional regulation and thus chose to fluorescently tag the repressor. The fluorescent protein mCherry was chosen due to minimal auto-fluorescence from MOPS minimal media and minimal spectral overlap with our reporter gene YFP. Furthermore, a dimeric Lac-mCherry fusion construct is known to be functional *in vivo* (Lau et al., 2004). The goal is to measure raw mCherry fluorescence and  $OD_{600}$  in growing *E. coli* cells and convert those measurements to an intracellular concentration of lac repressor (Fig. 2).

A linear relationship was established for  $OD_{600}$  and cell count. We estimate the volume of *E. coli* growing in glucose supplemented minimal media to be  $1 \times 10^{-15}$  L (Kubitschek & Friske, 1986). We then measured  $OD_{600}$ , calculated the number of cells and multiplied by volume of the cell to calculate the fraction of the well that is intracellular. A linear relationship was also established for purified Lac-mCherry fluorescence and concentration of Lac-mCherry.

We assume all of the Lac-mCherry is intracellular; therefore we divided the Lac-mCherry concentration by the fraction of volume that is intracellular. Using this method, we can quickly and accurately measure *in vivo* Lac-mCherry concentrations.

221 Intracellular Lac-mCherry concentration in EPB229 cells

EPB229 cells expressing Lac-mCherry and the reporter plasmid were grown in varying concentrations of the inducer IPTG. Intracellular concentration of Lac-mCherry was calculated

from mCherry fluorescence and  $OD_{600}$  and found to be  $664 \pm 90$  nM at mid-log growth phase

- 225 ( $OD_{600} = 0.6$ ). As expected for a constitutively expressed gene, minimal variation was seen with 226 IPTG and cell growth (Fig. 3A).
- 227 We then converted to molecules per cell,

$$6.6x10^{-7}M*1x10^{-15}\frac{L}{cell}*6.022x10^{23}\frac{molecules}{mole} = 397\frac{molecules}{cell}$$
(40)

228 We have previously estimated the copy number of our plasmid to be  $\sim 10-20$  plasmids/cell 229 (Daber, Sharp, & Lewis, 2009). This corresponds to approximately 20-40 Lac-mCherry dimers per plasmid which agrees well with previous estimates of ~40 Lac repressor dimers per plasmid 230 231 for our promoter (Oehler et al., 1994).

#### 232 Measuring the In Vivo Regulation of YFP

In addition to mCherry fluorescence and OD<sub>600</sub> measurements, YFP fluorescence was measured in cells as a function of IPTG. Unregulated expression was established by measuring OD<sub>600</sub> and YFP in cells co-transformed with O1 YFP reporter and a plasmid which does not contain any repressor (pABD34). These positive control cells were grown in tandem with cells containing both reporter and repressor and grown in a variety of IPTG concentrations.

Positive controls showed no IPTG dependence as expected, so data from every sample was combined to determine an overall positive control polynomial fit. YFP fluorescence is seen to increase as cells grow as would be expected due to the increased number of cells per  $\mu$ L. We remove this bias and normalize regulated YFP expression by dividing by the positive control fit curve.

Normalized YFP expression was then measured as a function of  $OD_{600}$  and IPTG (Fig. 3B. Almost no OD<sub>600</sub> dependence can be noted in the induction profile. The YFP signal is 244 245 repressed without IPTG and is approximately  $1.7 \pm 0.2\%$  of unregulated expression. Upon 246 induction with saturating IPTG we see a robust YFP increase to approximately  $61 \pm 5\%$  of the 247 unregulated expression.

#### 248 Measuring the In Vitro Regulation of mRNA

249 While the *in vivo* experiment measures translation product (fluorescing YFP) we know 250 the lac repressor actually regulates mRNA production. Previously, our lab has determined a 251 linear relationship between mRNA and fluorescence protein signal allowing us to use 252 fluorescence as a proxy for mRNA regulation in vivo (Daber & Lewis, 2009). The situation in 253 vitro is reversed; it is much easier to measure mRNA production.

254 We used the Maxiscript T7 in vitro transcription kit (Ambion) which produces mRNA 255 from linearized DNA with a T7 promoter. We then measured incorporation of radioactive 256 labeled CTP into mRNA. The T7 promoter was modified to add an O1 operator DNA site and 257 we were able to modulate Lac-mCherry and IPTG concentrations. A positive control of 258 constitutive mRNA production is established by not adding any Lac-mCherry.

259 We first established that radioactively labeled mRNA was linearly observable by 260 constitutively producing mRNA and loading various dilutions onto polyacrylamide gels and 261 established that mRNA concentration was linearly related to the concentration of mRNA loaded 262 on the gel. Positive controls were included for every experiment and were used for

263 normalization. The additional benefit of *in vitro* transcription is the flexibility in dosing not only IPTG, but also Lac-mCherry. We exploited this flexibility by first titrating in Lac-mCherry without IPTG present and with saturating IPTG (1mM) (Fig. 4A). As expected, increasing concentration of Lac-mCherry decreases mRNA production. Furthermore, addition of IPTG returns mRNA signal to near constitutive levels.

269 We then titrated IPTG at a fixed Lac-mCherry concentration (Fig. 4B). The induction of 270 mRNA is seen to very closely resemble that of the *in vivo* data, but it is noticeably leakier. 271 Maximal repression was about  $7.8 \pm 1.3\%$  and maximal induction was approximately  $88 \pm 9\%$ .

#### 272 Modeling Using MWC Thermodynamic Equilibrium

Finally, we sought to simultaneously model the *in vivo* and *in vitro* data using the Monod, Wyman, and Changeux (MWC) model of thermodynamic equilibrium. Previously, we have relied upon approximate solutions of the lac genetic switch equilibrium to model *in vivo* induction profiles. This solution assumes that the total repressor concentration greatly exceeds operator concentration ( $[R]_{tot} >> [O]_{tot}$ ). This condition does not hold for our *in vitro* experiment where we titrated in Lac-mCherry nor would it necessarily be true in all *in vivo* systems. Therefore, we sought a solution to the equilibrium that held for every potential input. An assumption free solution to the MWC model was found and is solved in detail in the methods.

Using the assumption-free solution to measure thermodynamic parameters

Experimentally we know the total concentrations ( $[R]_{tot}$ ,  $[E]_{tot}$ ,  $[O]_{tot}$ ) and normalized transcription/expression ( $[O]/[O]_{tot}$ ). We want to measure the thermodynamic constants ( $K_{RR^*}$ ,  $K_{RE}$ ,  $K_{R^*E}$ ,  $K_{RO}$ ,  $K_{R^*O}$ ). This leaves 5 independent constants in the MWC model to fit to the experimental data. The large number of independent constants results in a myriad of non-unique solutions to the equations. This complication was limited by the following algorithm.

First, since it is widely reported to be effectively zero,  $K_{R^{*O}}$  was set to be very, very small (1x10<sup>-10</sup> nM<sup>-1</sup>). This leaves four independent parameters.

289 Next, it had been observed from previous studies that the ratio of  $K_{R^*E}$  to  $K_{RE}$  is well 290 defined when the concentration of repressor greatly exceeds that of operator. Under this 291 assumption, a simpler solution of the MWC equilibrium exists as previously reported (Daber, 292 Sharp, & Lewis, 2009). We isolated a subset of the *in vitro* data where this condition was true and used a non-linear least squares fitting algorithm to measure the ratio  $X = K_{R^*E}/K_{RE}$  as a 293 294 function of conformational equilibrium. The ratio was seen to asymptote at approximately 295 13.75. This value is then used to reduce the number of independent constants to 3 (K<sub>RR\*</sub>, K<sub>RE</sub>, and 296 K<sub>RO</sub>).

297 We then simultaneously fit the *in vitro* data to obtain the best fit thermodynamic 298 parameters using a non-linear least squares algorithm in Matlab (Table 1). The model accurately 299 fits both the lac repressor (Figure 4A) and IPTG doping (Figure 4B) in vitro transcription experiments. The fit values agree well with values obtained in the literature with the exception 300 301 of repressor-DNA affinity. The repressor-DNA affinity ( $K_{RO}$ ) was measured to be  $0.4 \pm 0.2$  nM<sup>-1</sup>. 302 This is significantly weaker than the 100-3333 nM<sup>-1</sup> that has been measure previously (Sharp, 303 2011). It does agree well with an estimated value of 1 nM<sup>-1</sup> for lac repressor-DNA affinity that prevails under conditions within the E. coli cell (Müller-Hill, 1996). The thermodynamic 304

equilibrium value  $(6.3 \pm 3.3)$  does not significantly differ from that measured previously by our group. The repressor-IPTG affinity  $(7.6 \times 10^{-4} \pm 2.5 \times 10^{-4} \text{ nM}^{-1} \text{ for the higher affinity}$ conformation) was found to be slightly higher than previously published values  $(2.3 \times 10^{-4} \text{ nM}^{-1})$ but it is generally within agreement. The ratio of affinities for the two conformations (13.7) was in good agreement with previously measured values.

310 Using the in vitro thermodynamic parameters to predict in vivo genetic regulation

The raison d'être for *in vitro* measurements is to inform what is occurring *in vivo*. One of the central difficulties in using *in vitro* measurements is the lack of a well enough defined *in vivo* system to directly compare it with. Furthermore, a model is required which can accurately function in both circumstances and provide useful predictions. We then seek to fully define our *in vivo* experiment to model it with the *in vitro* determined thermodynamic parameters.

We estimate the copy number of our operator reporter plasmid to be  $\sim 20$  copies per cell (Daber, Sharp, & Lewis, 2009). This then gives us,

$$[O]_{tot} = \frac{20 \text{ molecules}}{6.02 \times 10^{23} \frac{\text{molecules}}{\text{mole}}} * \frac{1}{1 \times 10^{-15} \text{ L}} * 1 \times 10^{9} \frac{\text{nM}}{\text{M}} = 33 \text{ nM}$$
(41)

The strain of *E. coli* used has the lac genetic switch deleted from the genome; therefore lac permease is also deleted. It is then assumed that IPTG enters the cell through passive diffusion and has the same concentration as the media.

321 Figure 5A shows the simulated *in vivo* data (solid blue line) along with experimentally 322 determined values (blue squares). The model predicts both higher leakiness (2.7% predicted 323 versus  $1.7 \pm 0.2\%$  observed) and higher maximal induction (80% predicted versus  $61 \pm 5\%$ 324 observed) than is measured in vivo. This indicates that there are additional effects not being accounted for in the in vitro data. It has been postulated that non-specific DNA binding of 325 326 repressors could play a significant role (Tungtur et al., 2011), however this should have the effect 327 of decreasing the effective lac repressor concentration since the non-specific DNA will 328 competetively bind with operator DNA for lac repressor. We see the opposite in our data; the lac 329 repressor concentration appears higher in vivo than we are measuring.

There is a known molecular crowding effect in living cells due to the density of molecules which will increase the *effective* concentration of molecules. We can quickly model the effect of crowding by decreasing the available space for the lac repressor and estimating its effective concentration,

$$[R]_{tot}^{eff} = \frac{[R]_{tot}}{\% \text{ available space}}$$
(42)

Figure 5B shows the effect of including molecular crowding on the predicted *in vivo*induction curve. The model shows excellent agreement with experiment at a molecular
crowding of 40-60% which estimates effective *in vivo* repressor concentration to be 1.1-1.6 μM

337 (Leakiness:  $1.3 \pm 0.3\%$  predicted versus  $1.7 \pm 0.2\%$  observed; Maximal expression:  $67 \pm 4\%$ 338 predicted versus  $61 \pm 5\%$  observed). Furthermore, this value agrees well with estimates of 20%-339 40% available space *in vivo* (Kubitschek & Friske, 1986).

340 Since there is a notable deviation in repressor-DNA affinity with previous in vitro 341 measurements, the same analysis was carried out for the three curated data sets from Sharp 342 (Sharp, 2011). Using the values from the literature, we find that they do not in any case come 343 close to replicating our in vivo data (Fig. 5A, orange dashed, purple dotted line, and solid green 344 lines). The DNA affinities are much too high for the measured DNA and repressor 345 concentrations. At these affinities the switch is essentially completely off and cannot be induced 346 with any concentration of IPTG. Crowding only enhances the deviation from experiment as it 347 further increases the concentration of repressor.

3 *Simulating native* in vivo *lac genetic switch phenotype* 

The thermodynamic constants from our *in vitro* data better represents our *in vivo* model system. The question then is: which set of thermodynamic parameters could effectively regulate the native lac genetic switch?

Essentially we have rebuilt the lac operon with the *lacZ*, *lacY* and *lacA* polycistronic message replaced by the reporter gene YFP and the dimeric lac repressor constitutively expressed by its native promoter. We have a higher copy number of both the reporter and repressor plasmids (~20 copies per cell) which increases both the operator and repressor concentrations above that normally found in the cell. A secondary deviation is the removal of the tetramerization domain and multiple operator DNA sites (O2 and O3 additionally exist on the genome) which simplifies our analysis. The cooperativity of the native tetrameric lac repressor is known to decrease leakiness approximately 10-fold, so we might expect a dimeric lac repressor with one operator (O1) to have some leakiness in its repression (Oehler et al., 1994).

As previously mentioned, *in vivo* lac repressor dimer concentration was measured to be ~40 dimers per cell, which gives,

$$[R]_{tot} = \frac{40 \text{ molecules}}{6.02 \text{ x} 10^{23} \frac{\text{molecules}}{\text{mole}}} * \frac{1}{1 \text{ x} 10^{-15} \text{ L}} * 1 \text{ x} 10^{9} \frac{\text{nM}}{\text{M}} = 66 \text{ nM}$$
(43)

363

And we know there is one operator per cell,

$$[O]_{tot} = \frac{1 \text{ molecules}}{6.02 \text{ } \text{x} 10^{23} \frac{\text{molecules}}{\text{mole}}} * \frac{1}{1 \text{x} 10^{-15} \text{ L}} * 1 \text{x} 10^{9} \frac{\text{nM}}{\text{M}} = 1.7 \text{ nM}$$
(44)

Using these values, along with the experimentally determined binding constants derived
from this study and those curated by Sharp, we can simulate dimeric lac repressor induction
curves at native conditions. Figure 6A shows that the values determined in this study predict a

leaky repressor that is maximally inducible. The much higher DNA affinities of the curated datasets all produce over-repressed curves that do not show good induction.

The over-repression is even more prominent as cell crowding is considered. Using the value of 40%, which gives  $R_{tot} = 66 \text{ nM} / 0.4 = 165 \text{ nM}$ , we find that the over-repression of the high affinity DNA sets all produce curves that weakly induce or do not induce at all (Fig. 6B). The predicted curve using our thermodynamic parameters again provides reasonable induction (~10% leakiness up to ~95% maximal induction). While this level of leakiness would be intolerably high for efficient regulation of the lac operon, the restoration of the tetramerization domain would significantly decrease the leakiness while minimally impairing inducibility.

If we consider the lowest possible concentration of lac repressor (1 molecule/cell;  $R_{tot} =$  1.7 nM; with 40% crowding  $R_{tot} = 4.25$  nM) we find that second curated data set does produce reasonable induction curves, even if 40% crowding is taken into consideration (Fig 6C and Fig. 6D). Unfortunately, in this regime the binding would be highly stochastic and hence noisy, which would not produce stable repression. Furthermore, this level of repressor expression does not agree with published values. While it is technically possible for these affinities to be accurate, it is highly improbable. The first and third data sets would require less than 1 molecule of dimeric lac repressor per cell to be functionally useful according to our model.

Given the wide range of repressor-operator DNA affinities (100nM - 3333nM) it can be reasonably concluded that these values must contain significant artifacts from the experimental techniques. Techniques such as gel shift assays, where molecular "caging" effects are known to be significant, and nitrocellulose filter binding assays, where the binding is removed from the solution phase, were used to create the curated data sets. Our measurement of repressor-DNA binding affinity did require an indirect measurement, namely transcription, but it did occur in the solution phase. We attribute the difference in values to differences in experimental setup.

#### 391 Conclusions

392 We have reproduced the transcriptional regulation of the lac repressor dimer *in vitro* and 393 shown that it accurately reproduces the *in vivo* repression of YFP under control of the lac 394 repressor. Accurate modeling of the *in vivo* data required an estimate of 40-60% cellular 395 crowding in the cell, which agrees with previous estimates. Non-specific DNA binding and IPTG uptake did not appear to have any significant effect. Crowding could be tested in vitro through 396 397 crowding agents such as bovine serum albumin (BSA) or polyethylene glycol (PEG) (Ellis, 2001). Alternative explanations are potentially possible such as fluctuations in the size of the E. 398 399 *coli*. What is essentially important is that the concentration of lac repressor in the cell greatly 400 affects the maximal induction given our thermodynamic parameters. The curve is extremely 401 sensitive in that region to changes in repressor concentration. So only an approximately two-fold 402 increase in repressor concentration is sufficient to replicate the *in vivo* data. Whether the lac 403 repressor concentration is increased by molecular crowding or by decreased E. coli volume 404 would have to be tested by further experiments.

The measured thermodynamic binding parameters match well for IPTG binding and
conformational equilibrium, except there is significantly lower repressor/operator DNA affinity
measured (by approximately 3-4 orders of magnitude). This discrepancy was modeled and it was

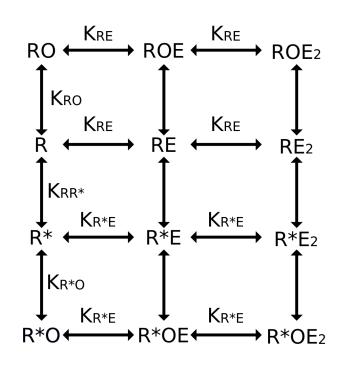
demonstrated that the affinity measured in this study is capable of reproducing not only the *in vivo* data from this study, but also can predict reasonable induction curves at concentrations of
repressor and DNA that are naturally seen by *E. coli*. We therefore conclude that lac repressor
DNA affinity is significantly weaker than previous *in vitro* measures and more in line with the
estimates for repressor-DNA affinity at *in vivo* conditions where we do find good agreement with
previously published values.

Finally, this study highlights the difficulty in using *in vitro* data generated from experimental techniques that are divorced from conditions closer to that of the cell. Experimental artifacts may greatly overshadow actual values, which should come as no surprise in the case of lac repressor binding to operator DNA where the published binding constant has changed 33-fold as experimental techniques have changed. The difficulty in *in vitro* measurements is well known in the field as is evidenced by the large consideration given to differences in buffer conditions (Ha et al., 1992), DNA length (Khoury et al., 1990), and even hydrostatic pressure (Royer, Chakerian, & Matthews, 1990). Techniques such as gel filtration or nitrocellulose filter binding assays are excellent at differentiating binding strength between point mutants; they are limited in comparison with *in vivo* results. Using experimental setups which more closely mimic the *in vivo* system can significantly improve the ability of the predictive capabilities of *in vitro* experiments. They do come with the caveat that the data interpretation is not as straightforward as simple binding experiments.

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#### Figure 1. Monod, Wyman, and Changeux (MWC) model of thermodynamic equilibrium.

This model identifies two primary structural conformations of the lac repressor (R and R\*): the R
state has high operator DNA (O) affinity and the R\* state has low operator DNA affinity.
Addition of effector (E) alters the effective equilibrium between the two states allowing for an
increase or decrease in amount of operator DNA bound. Fraction of bound operator is considered

439 a proxy for transcription; unbound operator can be freely transcribed. Thermodynamic binding

and conformational equilibrium constants are fully defined in the methods.

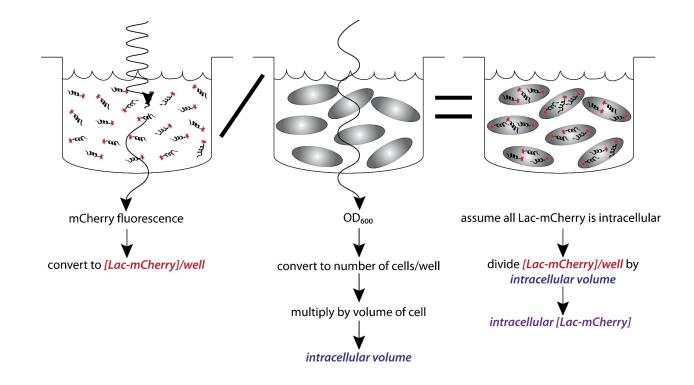
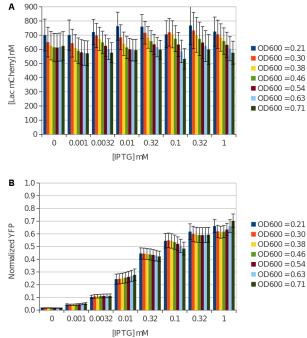


Figure 2. Measuring intracellular Lac-mCherry concentration. Raw mCherry fluorescence 442 443 and OD<sub>600</sub> are measured on a plate reader. Calibration curves for both were established given our 444 experimental setup (cell line, plasmids, media, amount of sample loaded, plates and plate reader). 445 Raw fluorescent signal is converted to concentration of Lac-mCherry per well. Raw OD<sub>600</sub> signal 446 is converted to the fraction of well volume that is intracellular. Dividing Lac-mCherry well 447 concentration by intracellular volume fraction effectively concentrates the Lac-mCherry to be 448 intracellular. These two measurements, combined with the appropriate calibrations, allow a quick 449 and accurate measurement of intracellular Lac-mCherry concentration.



# 451 Figure 3. *In vivo* Lac-m

## 51 Figure 3. *In vivo* Lac-mCherry and YFP regulation show no growth dependence. (A) Lac-

452 mCherry was calculated for growing *E. coli* cells and found to have minimal  $OD_{600}$  dependence.

453 As expected for a constitutively expressed gene, there is no change in Lac-mCherry

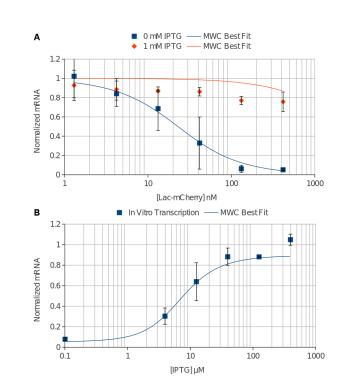
454 concentration with increasing IPTG concentration. (B) Normalized YFP was simultaneously

455 measured and again no  $OD_{600}$  dependence was found throughout the exponential growth phase. In

456 stark contrast to the Lac-mCherry concentration, a distinct induction profile is measured for YFP

457 as a function of IPTG.





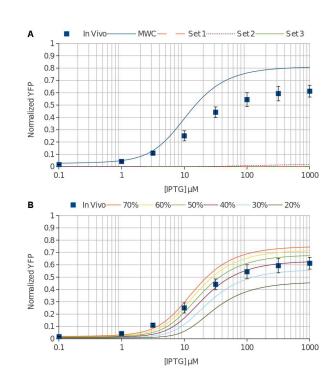
459 Figure 4. In vitro transcription controlled by the lac repressor is accurately fit by the MWC 460 model. (A) Lac-mCherry was added at varying concentrations with 11nM O1 DNA and mRNA 461 was quantitated (blue squares). The repression was relieved upon addition of 1mM IPTG (orange 462 diamonds). The data was globally fit by the MWC model and an accurate solution was found for 463 the Lac-mCherry titration (solid blue line). The model predicts higher induction than was 464 measured experimentally (solid orange line). (B) IPTG was added at varying concentrations with 465 333nM Lac-mCherry and 11nM O1 DNA and again mRNA was quantitated (blue squares). A 466 robust induction profile was measured showing induction up to approximately 80% of 467 constitutive expression. The global fit also accurately fits the IPTG titration data (solid blue line).

	This study	Sharp, and	Daber, Sochor, and Lewis¥	- ·	Sharp, Set 2 ‡		
$K_{RR*} = [R*]/[R]$	6.3 ± 3.4	$2 \pm 0.5$	$5.8 \pm 0.07$				
K <sub>RO</sub>	0.42 ±						
$(nM^{-1})$	0.21			3330	100	1510	1
$K_{\text{RE}}$	5.6x10 <sup>-5</sup> ±		$6x10^{-5} \pm$				
(nM <sup>-1</sup> )	1.8x10 <sup>-5</sup>		$2x10^{-7}$				
$K_{R^{\ast}E}$	$7.6 \times 10^{-4} \pm$		$5 \times 10^{-4} \pm$				
(nM <sup>-1</sup> )	$2.5 \times 10^{-4}$		$5x10^{-6}$	2.3x10 <sup>-4</sup>	2.3x10 <sup>-4</sup>	2.3x10 <sup>-4</sup>	
K <sub>R*0</sub>							
(nM <sup>-1</sup> )	1.0x10 <sup>-10</sup>						
R <sub>tot</sub>							
(nM) [with 40% crowding]	-						
$r = K_{RO} * R_{tot}$ [with 40% crowding]	278 [697]	150 ± 50	150 ± 50				
$\begin{array}{l} X = \\ K_{R^{*E}}  /  K_{RE} \end{array}$	13.7 ± 0.13	15 ± 3	8.28				

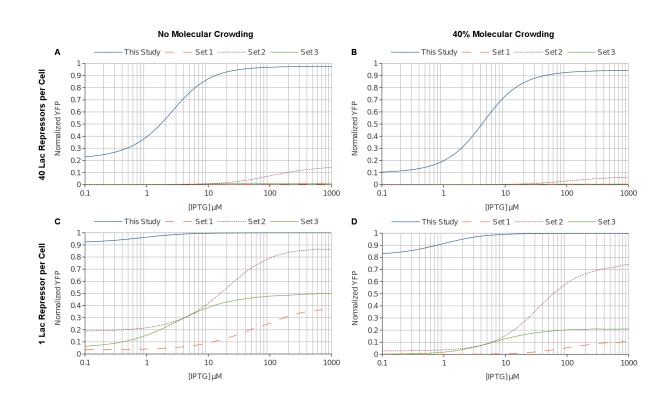
# 469 Table 1. Fit values from the MWC models compared with literature values. All fit

- 470 parameters agree with the exception of repressor-operator DNA affinity ( $K_{RO}$ ). †(Daber, Sharp, &
- 471 Lewis, 2009), ¥(Daber, Sochor, & Lewis, 2011), ‡(Sharp, 2011), §(Müller-Hill, 1996).

472



473 Figure 5. In vivo regulation by the lac repressor is accurately predicted with molecular 474 crowding. (A) YFP under control of the lac repressor was measured in E. coli cells at varying 475 concentrations of IPTG (blue squares). We used the measured intracellular concentration of the 476 lac repressor (660nM) and the fit values from *in vitro* transcription to predict the *in vivo* 477 induction curve with the MWC model (solid blue line). The model predicts more YFP signal at 478 all concentrations of IPTG. Our repressor-DNA affinity was much lower than previously 479 published values, so we also modeled three curated data sets (Sharp, 2011) (dashed orange, 480 dotted purple, and solid green lines). All three predict greatly over-repressed YFP expression and 481 do not fit the *in vivo* data. (B) Molecular crowding is known to play a significant role in cells. We 482 modeled this by estimating the available volume in percentage for our repressor and calculated 483 an effective repressor concentration. We modeled several percentages and 40-60% available 484 volume (solid purple, green and yellow lines) accurately reproduces the *in vivo* regulation from 485 the *in vitro* transcription derived thermodynamic constants. 40% crowding corresponds to an 486 effective repressor concentration of 1.6µM.



488 Figure 6. Simulating a simplified lac operon from *in vitro* derived thermodynamic

489 constants. The correct repressor-DNA affinities must be able to provide robust switching under 490 conditions naturally experienced by E. coli. With this in mind, we modeled a dimeric lac 491 repressor regulating a gene with a single operator sequence. (A) The natural lac promoter makes 492 ~66nM of lac repressor dimer and one operator is at ~ 1.7nM in the cell. We modeled these 493 conditions for the thermodynamic parameters from this study and for the three curated data sets 494 of Sharp. The predicted curve from this study shows a reasonable repression and induction 495 profile (solid blue line). Only Set 2 from Sharp is weakly inducible (dotted purple line). (B) 496 Including molecular crowding (40% available volume) enhances the situation. The curated data 497 sets do not make useful switches. Alternately, the predicted induction curve from *in vitro* 498 transcription derived constants shows a leaky switch that induces very well (solid blue line). (C) 499 We next sought to model the minimal possible repressor to find a condition where the curated 500 data sets produce reasonable induction curves. 1 molecule of dimer per cell (~1.7nM) does show good induction profiles for set 2 (dotted purple line) and set 3 (solid green line). Set 1 still shows 501 502 a switch that can marginally be induced and would likely not be useful (dashed orange line). (D) 503 Molecular crowding effects again enhance the repressor concentration and only set 2 could 504 reasonably regulate a gene (dotted purple line). The values from this study (solid blue line) 505 predict a very leaky switch. Although the second curated set could effectively regulate the gene 506 at this concentration, in reality a single dimer and single operator DNA binding would be 507 dominated by stochastic events creating an inherently unstable switch.

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