Genome concentration limits cell growth and modulates proteome composition in *Escherichia coli*

Jarno Mäkelä[1,2,3,†], Alexandros Papagiannakis[1,2,†], Wei-Hsiang Lin[1,2,&], Michael C. Lanz[4,5,&], Skye Glenn[2,4], Matthew Swaffer[4,¶], Georgi K. Marinov[6], Jan M. Skotheim[4,5], Christine Jacobs-Wagner[1,2,4,7*]

[1]Howard Hughes Medical Institute, Stanford University, Stanford, CA 94305, USA

[2]Sarafan Chemistry, Engineering, and Medicine for Human Health Institute, Stanford University, Stanford, CA 94305, USA

[3]Institute of Biotechnology, Helsinki Institute of Life Science, University of Helsinki, Helsinki, Finland

[4]Department of Biology, Stanford University, Stanford, CA 94305, USA

[5]Chan Zuckerberg Biohub, Stanford, CA 94305, USA

[6]Department of Genetics, Stanford University, Stanford, CA 94305, USA

[7]Department of Microbiology and Immunology, Stanford School of Medicine, Stanford, CA 94305, USA

[¶]Current address: Wellcome Centre for Cell Biology, University of Edinburgh, Edinburgh, EH9 3BF, UK

[†]These authors contributed equally to this work.

[&]These authors contributed equally to this work.

[*]For correspondence: jacobs-wagner@stanford.edu

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ABSTRACT

Defining the cellular factors that drive growth rate and proteome composition is essential for understanding and manipulating cellular systems. In bacteria, ribosome concentration is known to be a constraining factor of cell growth rate, while gene concentration is usually assumed not to be limiting. Here, using single-molecule tracking, quantitative single-cell microscopy, and modeling, we show that genome dilution in *Escherichia coli* cells arrested for DNA replication limits total RNA polymerase activity within physiological cell sizes across tested nutrient conditions. This rapid-onset limitation on bulk transcription results in sub-linear scaling of total active ribosomes with cell size and sub-exponential growth. Such downstream effects on bulk translation and cell growth are near-immediately detectable in a nutrient-rich medium, but delayed in nutrient-poor conditions, presumably due to cellular buffering activities. RNA sequencing and tandem-mass-tag mass spectrometry experiments further reveal that genome dilution remodels the relative abundance of mRNAs and proteins with cell size at a global level. Altogether, our findings indicate that chromosome concentration is a limiting factor of transcription and a global modulator of the transcriptome and proteome composition in *E. coli*. Experiments in *Caulobacter crescentus* and comparison with eukaryotic cell studies identify broadly conserved DNA concentration-dependent scaling principles of gene expression.

INTRODUCTION

Cells regulate the intracellular concentration of various proteins and macromolecules to modulate the rate of essential cellular processes, including growth. In bacteria, cell mass and volume typically double between division cycles. Proportionality between biosynthetic capacity and biomass

accumulation results in exponential or near-exponential cell growth during the cell cycle (Campos et

al., 2014; Schaechter et al., 1958; Siegal-Gaskins and Crosson, 2008; Taheri-Araghi et al., 2015; Wang

et al., 2010). What drives exponential growth has been a longstanding question in the microbiology

field (Belliveau et al., 2021; Churchward et al., 1982; Ecker and Schaechter, 1963; Zhurinsky et al.,

2010). Quantitative studies on model bacteria such as *Escherichia coli* place the concentration of

ribosomes and their kinetics as the principal rate-limiting factors (Belliveau et al., 2021; Bosdriesz et

al., 2015; Koch, 1988; Scott et al., 2014, 2010). Most other cellular components essential for growth

are estimated to be at least an order of magnitude above the level required for proper enzymatic

reactions (Belliveau et al., 2021), indicating that they are well in excess in terms of metabolic

concentrations. Thus, translation is generally seen as the rate-governing process for cellular growth.

While the translocation rate of ribosomes poses an inherent limit on the growth rate of the cell,

protein concentrations are predominantly set transcriptionally at the promoter level, with tight

coordination between transcription and translation (Balakrishnan et al., 2022).

Whereas the importance of ribosome concentration in growth rate determination has been

extensively studied, a potential role for genome concentration has received less attention. An early

population study on an *E. coli* thymine auxotroph proposed that global transcription is not limited by

the concentration of the genome but is instead constrained by the availability of RNA polymerases

(RNAPs) (Churchward et al., 1982). However, the potential impact of DNA concentration on

determining the growth rate of *E. coli* or other bacteria has, to our knowledge, not been formally

tested. Interestingly, *E. coli* and *Bacillus subtilis* have been shown to display small but reproducible

deviations from exponential growth during the division cycle (Kar et al., 2021; Nordholt et al., 2020),

with the growth rate increasing after the initiation of DNA replication under some conditions.

Furthermore, at the population level, these organisms initiate DNA replication at a fixed cell volume

(mass) per chromosomal origin of replication (*oriC*) across a wide range of nutrient and genetic

conditions (Donachie, 1968; Govers et al., 2024; Si et al., 2017; Zheng et al., 2016), suggesting that

DNA concentration is an important physiological parameter for these bacteria. In eukaryotes where

genome concentration is also tightly controlled (Ginzberg et al., 2015; Turner et al., 2012), a change

in DNA-to-cell-volume ratio has recently been demonstrated to remodel the proteome and promote

cellular senescence (Crozier et al., 2023; Foy et al., 2023; Lanz et al., 2023, 2022; Manohar et al., 2023;

Neurohr et al., 2019; Wilson et al., 2023).

In this study, we combined single-cell and single-molecule microscopy experiments with

tandem-mass-tag (TMT) mass spectrometry, RNA sequencing (RNA-seq), and modeling to investigate

the potential physiological role of genome concentration in cell growth and proteome composition in

E. coli.

RESULTS

Growth rate correlates with the genome copy number.

To examine the potential effect of DNA content on the growth rate of *E. coli*, we used two CRISPR

interference (CRISPRi) strains with arabinose-inducible control of expression of dCas9 (Li et al., 2016;

Si et al., 2017). One strain expressed a single guide RNA (sgRNA) against *oriC* where sequestration by

dCas9 binding prevents the initiation of DNA replication to produce cells with a single copy of the

chromosome (Si et al., 2017). These cells, referred to as "1N cells" below, grew into filaments as a

block in DNA replication prevents cell division, but not cell growth, from occurring (Figure 1A) (Carl,

1970; Si et al., 2017; Withers and Bernander, 1998). The second CRISPRi strain, which served as a

comparison, expressed a sgRNA against the cell division protein FtsZ. FtsZ depletion blocks cell division

while allowing DNA replication to proceed (Addinall et al., 1996; Li et al., 2016). Ongoing growth

resulted in filamenting cells with multiple replicating chromosomes, hereafter referred to as "multi-

N cells" (Figure 1A). For both strains, we used time-lapse microscopy to monitor growth at the single-

cell level at 37°C in M9 minimal medium supplemented with glycerol, casamino acids, and thiamine

(M9glyCAAT). Cell area (A) was automatically detected from phase-contrast images using a deep

convolutional network (Wiktor et al., 2021), and the absolute growth rate ($\frac{dA}{dt}$) was determined by

calculating the difference in cell area between frames. The relative growth rate ($\frac{1}{A}\frac{dA}{dt}$), which is

constant for exponential growth, was calculated by dividing the absolute growth rate by the cell area.

We used WT cells to verify that the transition from liquid cultures to agarose pads led to stable growth

from the start of image acquisition (Figure 1 – figure supplement 1).

As the induced CRISPRi *oriC* phenotype is not fully penetrant, we limited our analysis to 1N

cells that contained a single DNA object (nucleoid) labeled by a mCherry fusion to the nucleoid-binding

protein HupA (referred to as HU below). To confirm this 1N chromosome designation, we used a

CRISPRi *oriC* strain that expresses HU-CFP and carries an *oriC*-proximal *parS* site labeled with ParB-

mCherry (Figure 1 – figure supplement 2), used here to determine the number of nucleoids and

chromosomal origins per cell. We found that 96 ± 1% (mean ± standard deviation, SD, three biological

replicates) of cells (n = 3378) with a single HU-labeled nucleoid contained no more than one ParB-

mCherry focus, indicative of a single *oriC*.

Using this methodology, we observed a significant difference in growth rate between 1N and

multi-N cells as shown in representative single-cell growth trajectories (Figure 1B) and in aggregated

absolute growth rate measurements (Figure 1C). In multi-N cells, the absolute growth rate rapidly

increased with cell area. In 1N cells, the absolute growth rate only moderately increased with cell area,

approaching an apparent plateau at large cell sizes (Figure 1C). As an independent validation, we used

an orthogonal system to block DNA replication using the temperature-sensitive mutant *dnaC2*, which

encodes a deficient DNA helicase loader at the restrictive temperature of 37°C (Carl, 1970; Withers

and Bernander, 1998). We observed that the relationship between absolute growth rate and cell area

in *dnaC2* cells with a single nucleoid was similar to that of 1N cells produced by the CRISPRi *oriC* system

(Figure 1D). This sub-exponential growth in 1N and *dnaC2* cells resulted in a relative growth rate that

decreased with cell area (Figure 1E). For multi-N cells, the relative growth rate was not perfectly

constant but appeared to increase somewhat with cell area (Figure 1E). It is unclear whether this slight

increase is biologically meaningful, as simulations show that a small inaccuracy in cell size from cell

segmentation can produce the appearance of super-exponential growth at large cell sizes (Figure 1 –

figure supplement 3). Regardless, and most importantly, the multi-N cells grew identically to WT

within the same cell size range while 1N cells grew significantly slower (Figure 1 – figure supplement

4).

The striking divergence in growth between 1N and multi-N cells of the same size suggested

that DNA concentration can affect growth rate. The difference in growth rate between 1N and multi-

N cells was already apparent in the physiological range of cell sizes when compared to WT cells (Figure

1 – figure supplement 4), suggesting that growth rate reduction occurs soon after DNA replication

fails to initiate. We confirmed that the slower growth of 1N cells did not depend on the time that cells

spent on agarose pads (Figure 1 – figure supplement 5A). We also ruled out that the growth reduction

was due to an induction of the SOS response or to an increased level in the nucleotide alarmone

(p)ppGpp, as inactivation of either stress pathway (through deletion of *recA* or *spoT/relA*, respectively)

in 1N cells made little to no difference to their growth rate (Figure 1 – figure supplement 5B).

We noticed that, even at the restrictive temperature, the *dnaC2* strain produced a sizeable

fraction of cells with more than one HU-mCherry-labelled nucleoid (Figure 1 – figure supplement 6A-

B), indicating that the temperate-sensitive effect on DNA replication is not fully penetrant. We took

advantage of this phenotypic "leakiness" to measure the growth rate of cells with different numbers

of nucleoids (and thus chromosomes) within the *dnaC2* population. We observed a notable difference

in growth rate between cells of 1, 2, and >2 nucleoids in the population, with each additional nucleoid

contributing to higher cellular growth at a given cell size (Figure 1F-G). This finding is consistent with

DNA-limited growth in which cellular growth rate increases with genome concentration. We obtained

similar results when we calculated absolute and relative growth rates based on extracted cell volumes

instead of areas (Figure 1 – figure supplement 7A-F), as cell width remained largely constant during

cell filamentation (Figure 1 – figure supplement 7G).

A growth rate dependency on genome concentration is unlikely to be a particularity of *E. coli*,

as we also observed a divergence in absolute and relative growth rates with increasing cell area

between 1N and multi-N cells of *Caulobacter crescentus* (Figure 1 – figure supplement 8A-B). We

generated filamenting 1N and multi-N *C. crescentus* cells by depleting the DNA replication initiation

factor DnaA (Gorbatyuk and Marczynski, 2001) and the cell division protein FtsZ (Wang et al., 2001),

respectively. We confirmed the 1N versus multi-N designation by visualizing the number of

chromosomal origins of replication (one versus multiple) per cell using the *parS*/ParB-eCFP labeling

system (Figure 1 – figure supplement 8C).

The concentration of ribosomal proteins remains relatively constant in genome-diluted *E. coli* cells.

Ribosome content is often proposed to explain the exponential growth of biomass in bacteria, with growth rate being directly proportional to ribosome concentration (Bremer and Dennis, 1996; Ecker and Schaechter, 1963; Scott et al., 2014, 2010). Therefore, we first quantified the fluorescence concentration of a monomeric superfolder green fluorescent protein (msfGFP) fusion to the ribosomal protein RpsB (expressed from the native chromosomal locus) in 1N and multi-N cells in M9glyCAAT as a function of cell area. We found it to be almost identical between the two CRISPRi strains and relatively constant across cell areas, regardless of DNA content (Figure 2A).

To exclude the possibility that the msfGFP tag altered the synthesis of RpsB or that this protein behaved differently from other ribosomal proteins, we adapted a TMT mass spectrometry (MS) method recently developed to examine cell size-dependent proteome scaling in yeast and human cells (Lanz et al., 2022). Note that, for the CRISPRi *oriC* strain, a minority (~10-15%) of cells have more than one nucleoid. These cells were excluded from the analysis of our single-cell microscopy experiments. However, this could not be done for the TMT-MS experiments, which provide population-level measurements. Therefore, for this TMT-MS section, we will refer to the CRISPRi *oriC* cell population as "1N-rich" cells, instead of only "1N" cells. Using the TMT-MS approach, we found that the relative concentration of all (54) high-abundance ribosomal proteins (including untagged RpsB) remained approximately constant across all sizes of 1N-rich cells, and was similar between 1N-rich and multi-N cells (Figure 2B). Only the relative concentration of the ribosomal protein L31B, a stationary phase paralog of the more prevalent exponential phase ribosomal protein L31A (Lilleorg et al., 2019), significantly decreased in 1N cells (Dataset 1). Thus, the concentration of ribosomal proteins does not explain the difference in growth rate between cells with different ploidy.

The fraction of active ribosomes is reduced in genome-diluted cells.

To more specifically probe the translational activity of ribosomes in 1N cells, we performed single-

molecule tracking in live cells growing in M9glyCAAT. Ribosomes are expected to exhibit at least two

different dynamic states: slow mobility when active (i.e., engaged in translation on the mRNA, often

in polyribosome form), and faster mobility when inactive ribosomes (or ribosomal subunits) are

diffusing in the cytoplasm (Mohapatra and Weisshaar, 2018; Sanamrad et al., 2014). To track

ribosomes, we introduced a HaloTag fusion to RpsB (through genetic modification at the endogenous

chromosomal locus) and labeled the HaloTag using the membrane-permeable Janelia Fluor 549 (JF549)

fluorescent dye (Grimm et al., 2015). We quantified the apparent diffusion coefficient (D_a) of single-

molecule tracks in WT cells, as well as in 1N and multi-N cells at multiple time points following CRISPRi

induction (Figure 2C). We found that the distribution of D_a in multi-N cells of all sizes (~2-10 μm^2) was

similar to that in WT cells despite the considerable differences in cell sizes. In contrast, 1N cells

displayed distributions clearly distinct from WT and multi-N cells, gradually shifting toward faster

mobilities (higher D_a) with increasing cell size. This shift suggests that ribosome activity is altered in

1N cells.

Gaussian fitting of the D_a logarithmic data in WT cells revealed two predominant dynamic

states of ribosomes: a slow-diffusing and a fast-diffusing state, representing 77 ± 1% (mean ± standard

error of the mean (SEM)) and 20 ± 1% of the ribosome population, respectively (Figure 2D). In addition,

we observed a small fraction (3.2 ± 0.5%) of faster-moving molecules with D_a expected for freely-

diffusing proteins (Banaz et al., 2019; Elowitz et al., 1999), likely indicative of a small pool of free RpsB-

HaloTag proteins (i.e., not assembled into ribosomes). To confirm that the slow-diffusing fraction

corresponded to translationally active ribosomes, we showed that this fraction nearly vanished (down

to 1.10 ± 0.02%) when cells were depleted of mRNAs following 30 min treatment with the

transcription inhibitor rifampicin (Figure 2 – figure supplement 1). The estimated fraction (~77%) of

active ribosomes in untreated cells was in good agreement with previous single-molecule and

biochemical studies under similar growth conditions (Forchhammer and Lindahl, 1971; Mohapatra

and Weisshaar, 2018; Sanamrad et al., 2014).

Upon fitting the D_a values of ribosomes in WT and 1N cells (Figure 2E), we observed a

significant reduction in the slow-diffusing ribosome population in 1N cells of increasing area (Figure 2

– figure supplement 2). Quantification of the active (slow-diffusing) ribosome fraction per cell

revealed that 1N cells have overall lower ribosome activity than WT cells, and that ribosome activity

decreases monotonically with increasing cell area (Figure 2F). In contrast, ribosome activity in multi-

N cells remained the same as in WT across different cell sizes (Figure 2G).

To estimate the total number of active ribosomes per cell, we multiplied the total amount of

ribosomes by the fraction of active ribosomes and plotted the result as a function of cell area (Figure

2H). We found that the difference in the total number of active ribosomes between 1N and multi-N

cells matches the observed difference in growth rate (Figure 2H), indicating that cell growth rate is

directly proportional to the increase in total active ribosomes. Altogether, the results are consistent

with the hypothesis that DNA limitation decreases total ribosome activity, which, in turn, reduces the

growth rate.

Genome dilution reduces the activity of RNA polymerases.

We reasoned that the observed changes in ribosome activity in 1N cells may reflect the available

pool of transcripts. If true, we would expect the total activity of RNAPs to be reduced in 1N cells. The

total activity of RNAPs in cells is determined by the concentration of RNAPs multiplied by the fraction

of active RNAPs. Therefore, we first determined whether RNAP concentration was lower in 1N cells

relative to multi-N cells by quantifying the fluorescence intensity of a functional fusion of YFP to the

RNAP β' subunit (encoded by *rpoC*) expressed from its native chromosomal locus. As expected, RNAP

concentration remained constant in multi-N cells (Figure 3A). In 1N cells, the RNAP concentration

increased with cell size (Figure 3A), the opposite of what would be expected to explain the growth

rate defect. We confirmed this increasing trend in concentration for other protein subunits of the

core RNAP and the primary sigma factor σ^{70} (encoded by *rpoD*) using TMT-MS (Figure 4B), clearly

demonstrating that the abundance of RNAPs was not the limiting factor.

To quantify RNAP activity in 1N and multi-N cells, we performed single-molecule tracking in

live cells using a functional fusion of HaloTag to the β' protein subunit RpoC labeled with the JF549

dye. As expected, the D_a values of RpoC-HaloTag in multi-N cells were distributed similarly to those in

WT cells (Figure 3C). In contrast, the distribution in 1N cells changed gradually toward higher D_a values

(faster mobility) with increasing cell size (Figure 3C). As with ribosomes, RNAPs primarily exhibited

two major states of diffusivity (Figure 3D): a slower-diffusing fraction (49 ± 4%; mean ± SEM) and a

faster-diffusing fraction (49 ± 4%), likely representing transcriptionally active RNAPs and inactive,

diffusing RNAPs, respectively. A small fraction of RpoC-HaloTag (2 ± 0.1%) diffused very fast, with D_a

values expected for free proteins, suggesting that it reflects the few β' proteins not assembled into

the RNAP core complex. Using rifampicin treatment, we confirmed that the slowest state corresponds

to RNAPs actively engaged in transcription (Figure 3 – figure supplement 1). In these rifampicin-

treated cells, the slow-diffusing fraction was reduced to 13 ± 4%. Rifampicin does not prevent

promoter binding or open complex formation and instead blocks transcription elongation following

the synthesis of 3-nucleotide-long RNAs (Campbell et al., 2001). Thus, the observation that slow-

moving RNAPs did not completely disappear after rifampicin treatment is consistent with the

mechanism of action of the drug, leaving a fraction of RNAPs bound at promoter sites.

Unlike in WT and multi-N cells, the fraction of active RNAPs in 1N cells decreased

monotonically with increasing cell area (Figure 3F-G). However, because the RNAP concentration

simultaneously increased in 1N cells, it remained possible that the total amount of active RNAP, which

is the relevant metric of transcription activity, remained equal to that of multi-N cells. By calculating

the total amount of active RNAPs, we showed that the decrease in the active fraction in 1N cells was

not the mere result of the increase in RNAP concentration. Indeed, the total amount of active RNAPs

hardly increased with cell size in 1N cells whereas it increased proportionally with cell size in both

multi-N and WT cells (Figure 3H).

A recent study has shown that the intracellular concentration of Rsd, the anti-sigma factor of

σ^{70}, increases in WT cells under slower growth conditions, causing a reduction in global mRNA

synthesis (Balakrishnan et al., 2022). Therefore, we verified that the concentration of Rsd remains

approximately constant in both 1N-rich and multi-N cells based on our TMT-MS data (Figure 3 – figure

supplement 2), eliminating Rsd as a possible source of reduced RNAP activity in 1N cells. Instead, our

data supports the notion that substrate (DNA) limitation leads to a reduced transcription rate, which

reduces the pool of transcripts available for ribosomes.

Chromosome dilution reduces the concentration of transcripts.

To test the idea that genome dilution affects growth rate through transcript limitation, we performed

live-cell staining with SYTO RNASelect, a fluorogenic RNA-specific dye (Wu et al., 2020). This dye has

been proposed to preferentially bind mRNAs based on the observed decay of intracellular RNASelect

signal in *E. coli* during rifampicin treatment (Bakshi et al., 2014), which causes mRNA depletion.

However, a recent study has shown that the levels of ribosomal RNAs (rRNAs) also decrease in

rifampicin-treated cells (Hamouche et al., 2021), though at a slower rate than mRNAs. Therefore, to

complement the RNASelect staining experiments and examine the potential effect of genome dilution

specifically on rRNAs, we also carried out fluorescence in situ hybridization (FISH) microscopy on fixed

cells using EUB338-Cy3, a DNA probe complementary to an exposed region in the 16S rRNA (Amann

et al., 1990). For both experiments, we mixed 1N cells with multi-N cells of similar size ranges prior to

incubation with RNASelect or EUB338-Cy3 to mitigate variability in staining. We next imaged the

mixed populations and distinguished 1N cells from multi-N cells by examining the difference in

nucleoid number (one vs. multiple) per cell using HU-mCherry or DAPI as a DNA marker (Figure 4A).

Single cells were sampled to ensure that the cell area distributions of the two populations matched

(Figure 4 – figure supplement 1).

Comparison between the two sampled populations revealed a reduced concentration of

RNASelect signal by ~50% in 1N cells relative to multi-N cells for a cell size range of 4 to 10 μm^2 (Figure

4B-C). For a similar cell area range, the EUB338 signal concentration was reduced by only ~5%.

Furthermore, the RNASelect concentration ratio between 1N and multi-N cells displayed a rapid

exponential decay with increasing cell area, whereas the decrease in EUB338 concentration ratio was

considerably slower (Figure 4D).

To verify that the decrease in RNASelect signal in 1N cells was not caused by a global change

in membrane permeability to small molecules, we performed similar live-cell staining experiments

with the HaloTag dye JF549 in CRISPRi strains expressing RpoC-HaloTag (Figure 4 – figure supplement

2A). We matched the cell distributions between 1N and multi-N cells for fair comparison (Figure 4 –

figure supplement 2B). Because RpoC concentration increases with cell size in 1N cells relative to

multi-N cells (Figure 3A-B), we expected a similar increase in the ratio of JF549 signal between these

two cell types if the membrane permeability to small molecules remained unchanged. This is indeed

what we observed (Figure 4 – figure supplement 2C-E). In parallel, to examine the ability of our rRNA

FISH method to detect a reduction in 16S rRNA concentrations, we compared the EUB338 staining of

wildtype cells (MG1655) growing in M9 glycerol with or without casamino acids and thiamine

(M9glyCAAT vs M9gly), which results in a difference in growth rate of ~40% (Govers et al., 2024) due

to the expected lower concentration of ribosomes and thus 16S rRNAs in nutrient-poor media.

Consistent with this expectation, we found that the EUB338 concentration signal was reduced by ~50%

in M9gly relative to M9glyCAAT (Figure 4 – figure supplement 3). Given these validations, our results

in Figure 4 suggest that the RNASelect signal primarily reflects the bulk of mRNAs, and that the

concentration of mRNAs decreases more rapidly than that of rRNAs upon genome dilution.

DNA dilution can result in sub-exponential growth through mRNA limitation.

In a previous theoretical study, Lin and Amir (2018) considered distinct scenarios for gene expression.

Their model predicted that if DNA and mRNAs are in excess, cells will display exponential growth. On

the other hand, cells will adopt linear growth if DNA and mRNAs become limiting. Our experiments

showed that 1N cells indeed converge toward linear growth (toward slope = 0 in Figure 1C), though

the complete transition to linear growth required a large decrease in DNA concentration. To

quantitatively examine this transition from exponential to linear growth through genome dilution, we

developed two deterministic ordinary differential equation (ODE) models of the flow of genetic

information that include parameters for the fractions of active RNAPs and ribosomes. In these models,

the dynamics of mRNA (X) and protein (Y) numbers in the cell are described by

$$\frac{dX}{dt} = r_1 \alpha_{RNAP}(X,Y)Y - \delta X \qquad \text{(Eq.1)}$$

$$\frac{dY}{dt} = r_2 \alpha_{ribo}(X,Y)Y \qquad \text{(Eq.2)}$$

where r_1 is the bulk transcription rate normalized by the total protein number, r_2 is the bulk

translation rate normalized by the total protein number, and δ is the mRNA degradation rate. The

quantities $\alpha_{RNAP}(X,Y)$ and $\alpha_{ribo}(X,Y)$ are the fractions of active RNAPs and ribosomes expressed

as a percentage of the total RNAPs and ribosomes. For simplicity, we assumed that protein

degradation is negligible and that the cell volume and the number of rRNAs grow proportional to

protein Y (Balakrishnan et al., 2022; Lin and Amir, 2018). As a result, the rate of protein increase $\frac{dY}{dt}$

corresponds to the absolute growth rate and the relative protein increase rate $\frac{1}{Y}\frac{dY}{dt}$ corresponds to

the relative growth rate. For detailed description and estimation of the model parameters, see Table

1 and Appendices 1 and 2.

Based on the function form of $\alpha_{RNAP}(X,Y)$, we consider two ODE model variants. In model A,

we assumed that DNA is a limiting factor while RNAPs are not. In model B, both DNA and RNAPs were

considered as growth-limiting factors. In both models, higher DNA concentration increases the

probability that an RNAP will encounter and bind to a promoter. In model terms, α_{RNAP} (as well as

the downstream transcription rate) increases with DNA concentration. In model A, we examined the

effect of DNA limitation with minimal mathematical complexity by assuming that the proteome does

not change (see Materials and Methods). In model B, we considered RNAP kinetics (with three

different RNAP states: free, promoter-bound, and transcribing) based on the law of mass action (see

Materials and Methods and Appendix 3) and took into consideration the experimentally observed

increase in RNAP concentration in 1N cells (Figure 3A-B). For both models, α_{RNAP} depended on DNA

concentration.

We used these models to perform simulations and compared the results to our measurements,

starting with parameter values extracted or estimated from the *E. coli* literature (Table 2). In 1N cells,

the DNA amount was fixed to one genome while it scaled with cell volume in multi-N cells. The

parameters were then optimized to fit six experimental datasets simultaneously: cell growth rate, the

fraction of active RNAPs, and the fraction of active ribosomes in both 1N and multi-N cells (see

Materials and Methods and Appendix 4).

As shown in Figure 5A-D (model A) and Figure 5 – figure supplement 1 (model B), both models

performed similarly after parameter optimization. While the model curves (solid lines) did not

perfectly match the average behavior of our experimental results (open squares), they displayed

similar trends and fell within the variance of the single-cell data (dots). The models showed that multi-

N cells (blue) display balanced exponential growth while the 1N cells (yellow) exhibit sub-exponential

growth (Figure 5A and Figure 5 – figure supplement 1A), consistent with experiments. At the same

time, both models recapitulated the observed experimental trends in active fractions of both

ribosomes and RNAPs, which remained constant in multi-N cells while decaying gradually with DNA

concentration in 1N cells (Figure 5B-D and Figure 5 – figure supplement 1B-D).

The simulation results of 1N cells suggest the following cascade of events when DNA is limiting.

Lower DNA concentration results in fewer substrates for RNAPs, which reduces the transcription rate.

This results in a decrease in mRNA concentration. As mRNAs become limiting, the fraction of

ribosomes engaged in translation decreases. This, in turn, decreases the rate of bulk protein synthesis,

which decreases the relative growth rate. The greater the DNA dilution (through cell growth), the

more severe the downstream effects become, explaining the decay in relative growth rate in 1N cells

(Figure 5E).

Genome dilution rapidly limits RNAP activity under both nutrient-rich and -poor conditions, but the

extent of downstream effects on ribosome activity and cell growth can vary with the nutrient

condition.

In the relatively nutrient-rich M9glyCAAT condition, WT cells at birth are expected to have higher DNA

content than 1N cells on average due to overlapping DNA replication (Fossum et al., 2007). To examine

whether cells are also subject to DNA-limited transcription when multi-fork DNA replication is rare or

nonexistent, we examined the total RNAP activity of 1N cells relative to WT cells in two different

nutrient-poor media, M9gly and M9 L-alanine (M9ala). Abundance and diffusivity measurements of

RpoC-YFP-labeled RNAPs (Figure 6 – figure supplement 1) showed that the scaling between the total

amount of active RNAPs (i.e., global transcriptional activity) and cell area was strongly reduced in 1N

cells, even within the range of WT cell sizes (Figure 6A-B). Thus, genome dilution rapidly limits global

transcription in nutrient-poor (slow growth) conditions, as in richer (faster growth) conditions (Figure

3H).

In contrast, abundance and diffusivity measurements of fluorescently labeled ribosomes in

cells growing in M9gly and M9ala (Figure 6 – figure supplement 2) revealed that the total amount of

active ribosomes (i.e., bulk translational activity) and the absolute growth rate of 1N cells started to

deviate from proportional scaling with cell areas mostly when cells reached large (non-physiological)

sizes (Figure 6C-D). As a result, the difference in absolute growth rate between 1N and multi-N cells

was not as pronounced as in cells growing in the richer M9glyCAAT medium (Figure 6E-F vs. Figure

1C). This suggests that one or more cellular buffering activities may help mitigate the limitation of

DNA concentration on transcription in nutrient-poor media (see Discussion).

Genome dilution changes the composition of the transcriptome and proteome.

The fact that the relative concentrations of ribosomal proteins and RNAP subunits scaled differently

with cell area in 1N cells (Figures 2A-B and 3A-B) indicated that all genes are not equally impacted by

DNA dilution. In yeast and mammalian cells, a decrease in the DNA-per-volume ratio has recently

been demonstrated to alter the composition of the proteome, with some proteins increasing in

relative concentration while others become comparatively more diluted (Lanz et al., 2023, 2022). To

examine whether this effect may be conserved across domains of life, we used our proteomic TMT-

MS data on the CRISPRi strains to quantify the relative concentration of each detected protein across

cell areas following DNA replication or cell division arrest in M9glyCAAT. For each protein, we

calculated the relative change in concentration against the relative change in cell size through

regression fitting, yielding a slope value. A slope of zero indicates that the concentration of a protein

remains constant relative to the proteome whereas a slope of -1 (or 1) means that the relative

concentration is decreasing (or increasing) by two-fold with each cell size doubling (Figure 7A).

We found that the slope distribution was highly reproducible between biological replicates

(Figure 7 – figure supplement 1A-B) but drastically different between 1N-rich cells and multi-N cells

(Figure 7B, Dataset 1). In the control multi-N cells where the genome concentration does not change

with cell growth, the relative concentration of ~94% of the detected proteins (2217/2360) remained

roughly constant, with their relative concentrations decreasing or increasing by less than 20% per cell

size doubling (i.e., slopes > -0.2 or < 0.2; Figure 7B and Dataset 1). This suggests that protein amounts

largely scale with cell size, as generally assumed. However, in 1N-rich cells where the genome dilutes

with cell growth, the proportion of detected proteins with slopes near zero (> -0.2 or < 0.2) dropped

to ~37% (859/2360) (Figure 7B and Dataset 1). A principal component analysis on the relative protein

concentration during cell growth confirmed that the relative proteome composition changed

proportionally with genome dilution (1N-rich cells), whereas it remained constant when the DNA-to-

cell volume ratio was maintained (multi-N cells) (Figure 7C).

To examine whether the proteome scaling behavior stems from differential changes in mRNA

levels, we performed transcriptomic (RNA-seq) analysis on two biological replicates of 1N-rich cells at

different time points after induction of DNA replication arrest. The two replicates were strongly

correlated at the transcript level (Spearman ρ = 0.91, p-value < 10^{-10}, Figure 7 – figure supplement 1C).

We also found a strong correlation (Spearman ρ = 0.76, p-value < 10^{-10}) in scaling behavior with cell

area between mRNAs and proteins across the genome of 1N-rich cells (Figure 7D and Dataset 2),

indicating that most of the changes in protein levels observed upon genome dilution take place at the

mRNA level.

To investigate whether central processes may contribute to the observed transcriptome

remodeling during DNA limitation, we examined whether the RNA slopes correlate with gene-specific

rates of transcription initiation or mRNA degradation obtained from a published dataset (Balakrishnan

et al., 2022). Note that the reference dataset was generated from experiments on *E. coli* growing in

M9 glucose (M9glu) and not M9glyCAAT. However, both media give similar growth rates (Govers et

al., 2024) and our transcriptome measurements agree well with the reference data in terms of mRNA

abundance (Spearman ρ = 0.76, p-value < 10^{-10}, Figure 7 – figure supplement 2A). We found no

significant correlation between the rates of transcription initiation from the reference dataset and

RNA or protein slopes across genes (Figure 7 – figure supplement 2B-C). Consistent with this finding,

mRNA abundance was not a predictor of RNA slopes (Figure 7E). This was somewhat surprising as one

might anticipate highly transcribed genes to saturate with RNAPs faster than other genes. However,

we found that the mRNA degradation rate partly explains the variance in RNA and protein slopes.

Specifically, for genes producing short-lived transcripts (decay rate > 0.7 min^{-1}), the RNA and protein

slopes slightly negatively correlated with the rate of mRNA decay (Spearman correlation coefficient ρ

= -0.18, p-value < 10^{-10}, Figure 7F and Figure 7 – figure supplement 2D, Dataset 3). These results

suggest that genes that generate short-lived mRNAs are more susceptible to DNA limitation,

presumably because their mRNAs are more rapidly diluted with cell growth due to their fast decay.

Next, we examined whether genes reported to be essential for viability in three independent

studies (Gerdes et al., 2003; Goodall et al., 2018; Yamazaki et al., 2008) displayed biases in RNA and

protein slopes given the importance of their products for cell growth. Remarkably, essential genes,

which share similar mRNA decay rates as other genes (Figure 7 – figure supplement 2E, Mann-

Whittney p-value > 0.01), tended to exhibit superscaling behavior in 1N cells as shown by their

enrichment in positive RNA slopes regardless of the selected dataset (Figure 7G, Mann-Whittney p-

value < 10^{-10}). This suggests that cells have evolved regulatory mechanisms to minimize dilution of

mRNAs encoded by essential genes.

DISCUSSION

Our data suggest that DNA limitation in *E. coli* cells affects cell growth rate through modulation of

downstream transcription and translation activities (Figures 1-7 and associated figure supplements).

The fact that DNA limitation for cellular growth was also observed in *C. crescentus* (Figure 1 – Figure

supplement 8) is significant not only because this bacterium is distantly related to *E. coli*, but also

because it has a different pattern of cell wall growth and distinct control mechanisms of DNA

replication (Aaron et al., 2007; Banerjee et al., 2017; Frandi and Collier, 2019; Lasker et al., 2016;

Terrana and Newton, 1975). This suggests that DNA concentration may be a prevalent growth

constraint across bacterial species. It also helps explain why the timing of DNA replication in bacteria

is so robustly linked to cell volume across environmental and genetic conditions that affect cell size

(Donachie, 1968; Govers et al., 2024; Sauls et al., 2019; Si et al., 2017; Zheng et al., 2016).

Comparison with studies on eukaryotic cells suggests conservation of gene expression

principles across domains of life. For instance, in yeast, it has been shown that the global transcription

rate in G1-arrested cells is higher in diploids than haploids of similar sizes (Swaffer et al., 2023),

consistent with DNA concentration being a limiting factor for transcription. Furthermore, in both yeast

and mammalian cells, small G1-arrested cells display higher growth rate (or global RNA or protein

synthesis rate) per cell volume than large ones that have exceeded a certain volume (Cadart et al.,

2018; Liu et al., 2022; Neurohr et al., 2019; Zatulovskiy et al., 2022). This is likely due to a change in

genome concentration rather than a change in cell volume, as the relative growth rate is unaffected

in very large cells as long as they undergo a proportional increase in ploidy (Mu et al., 2020).

We found that even a relatively small dilution in DNA concentration—as expected in DNA

replication-arrested *E. coli* cells that are still within or close to physiological sizes—results in a

reduction of total RNAP activity in both rich and poor media (Figures 3H and 6A-B). Crude estimations

suggest that ≤ 40% DNA dilution is sufficient to negatively affect transcription (total RNAP activity) in

M9glyCAAT, whereas the same effect was observed after less than ~10% dilution in poor media

(M9gly or M9ala) (see Materials and Methods). Thus, cells appear to live at the cusp of DNA limitation

for transcription, especially under slow growth (nutrient-poor) conditions. This suggests that cells

make enough—but not too much—DNA, presumably because DNA replication is a costly process that

represents a significant fraction (~6% in minimal media) of the cellular energy budget (Neidhardt et

al., 1990).

What may be the implications of living close to DNA limitation? While *E. coli* carefully controls

its genome concentration across various conditions and growth rates at the population level

(Donachie, 1968; Govers et al., 2024; Si et al., 2017; Zheng et al., 2016), there remains variability in

DNA concentration at the single-cell level, with some cells initiating DNA replication at smaller or

larger cell volumes than others (Si et al., 2019; Witz et al., 2019). In future studies, it will be interesting

to explore whether this variability contributes to the known growth rate heterogeneity across isogenic

cells (Lin and Jacobs-Wagner, 2022; Wang et al., 2010). It is also tempting to speculate that changes

in genome concentration may, at least in part, contribute to the deviations from exponential growth

that have been reported during the division cycle of *B. subtilis*, *E. coli,* and stalked *C. crescentus*

progeny (Banerjee et al., 2017; Kar et al., 2021; Nordholt et al., 2020; Reshes et al., 2008). More

substantial forms of DNA dilution may occur under other circumstances. *C. crescentus* cells in

freshwater lakes often form long filaments during algal blooms in the summer months (Heinrich et al.,

2019). These filament cells are thought to be the result of a DNA replication arrest in response to the

combination of an alkaline pH, a depletion in phosphate, and an excess of ammonium (Heinrich et al.,

2019). Another example is illustrated by the Lyme disease agent *Borrelia burgdorferi*. This pathogen,

which forms long polyploid cells during exponential growth, experiences a progressive decrease in

genome concentration (up to eightfold) in stationary phase laboratory cultures through the gradual

loss of genome copies (Takacs et al., 2022).

In yeast cells, decreased mRNA turnover combined with increased RNAP II gene occupancy

helps mitigate DNA dilution on global transcriptional activities up to a certain (non-physiological) cell

volume, beyond which the compensation breaks down (Swaffer et al., 2023; Zhurinsky et al., 2010).

Such buffering activities, which are consistent with model predictions (Figure 4 – figure supplement

5) (Swaffer et al., 2023), may also be at play in *E. coli* in a growth medium-dependent manner. While

genome dilution rapidly impacted transcription in all tested media based on total RNAP activity

measurements (Figures 3H and 6A-B), we found that the negative impact on downstream processes—

total ribosome activity and cell growth—occurred later (i.e., mostly beyond physiological cell sizes) in

M9gly and M9ala (Figure 6C-F), in contrast to M9glyCAAT (Figures 1B-C and 2H). This suggests the

existence of mechanisms that compensate for DNA-limited transcription under slow growth such as

a decrease in mRNA decay, an increase in ribosome loading, and/or an increase in translation

elongation rate. Perhaps such buffering activities are not as effective under nutrient-rich conditions

due to the rapid mRNA dilution during fast growth. Testing these hypotheses will require future

experimentation.

Another remarkable similarity between bacteria and eukaryotes is the effect of genome

concentration on proteome composition. While protein abundance is typically assumed to scale with

cell size in bacteria, we found that this is true at the proteome level only when ploidy also scales

(Figure 7B). This requirement was also recently shown in yeast and mammalian cells (Lanz et al., 2023,

2022). This conservation of scaling principle further highlights the importance of genome

concentration in controlling protein expression.

What determines the scaling behavior of proteins in *E. coli* is not clear. We found that it largely

occurs at the mRNA level (Figure 7D), and that short-lived mRNAs are slightly more susceptible to

subscaling behavior (Figure 7F and Figure 7 – figure supplement 2D). Conversely, the majority of

essential genes (Gerdes et al., 2003; Goodall et al., 2018; Yamazaki et al., 2008) tended to display

superscaling behavior relative to the rest of the genome (Figure 7G, Dataset 3). This suggests the

existence of regulatory mechanisms that prioritize the expression of essential genes over less

important ones when genome concentration becomes limiting for cell growth.

While the scaling of proteins in 1N cells is largely driven by that of mRNAs (Figure 7D), we

found that protein slopes, but not RNA slopes, displayed a slight yet significant positive correlation

(Spearman ρ = 0.23, p-value < 10^{-10}) with *oriC* proximity for genes within 1.35 Mb from *oriC* (Figure 7

– Figure supplement 3A-B). Why and how this occurs is unclear, but it suggests that mRNA-

independent mechanisms (i.e., independent of mRNA synthesis or decay) also contribute to protein

scaling behavior. At the GO term level, we did not identify any specific trends in proteome changes

(Dataset 1). In eukaryotic cells, histones are known to scale in proportion with DNA rather than cell

size (Claude et al., 2021; Swaffer et al., 2021; Wiśniewski et al., 2014). As a result, their concentration

proportionally decreases (i.e., slope = -1) with growth in G1 phase. In *E. coli*, the relative abundance

of some nucleoid-associated proteins (H-NS, HU and Dps) decreased with genome dilution, while

others (IHF and Fis) displayed superscaling (protein slopes > 0) behavior (Figure 7 – figure supplement

4).

Given the prevalent use of *E. coli* in the biotechnological world, we hope that our findings will

be helpful to future bioengineering studies and growth rate optimization efforts. We show that

protein content and cellular growth depend on the ploidy-to-cell volume ratio (Figures 1 and 7). As

such, models of protein expression that take into consideration the DNA concentration and the active

number of RNAPs and ribosomes could provide a starting point to identify the parameter space that

leads to growth rate improvement. Experimentally, it will be important to determine which specific

genes exert the largest growth rate-limiting effect. In this context, the few essential genes with strong

subscaling behavior (large negative values of RNA and protein slopes) in 1N cells (Figure 7G, Dataset

3) suggest potential candidates for future studies given the rapid dilution of their mRNAs and proteins

relative to other genes.

MATERIALS AND METHODS

Bacterial strains and growth conditions

Bacterial strains and their construction can be found in Table 3. Oligomers used for polymerase chain

reaction (PCR) are listed in Table 4. Transductions and Gibson assemblies were performed as

described previously (Ely, 1991; Thomason et al., 2007).

E. coli strains were grown at 37°C in M9 minimal media with different supplements: 0.2%

glycerol, 0.1% casamino acids, and 1 µg/ml thiamine (M9glyCAAT); 0.2% glycerol (M9gly); or 0.2% L-

alanine (M9ala). For microscopy, cells were grown in culture tubes to stationary phase, diluted

10,000-fold, and grown until they reached an optical density (OD_{600}) between 0.05 and 0.2. For

imaging, cells were then spotted onto a 1% agarose pad on a glass slide prepared with the appropriate

M9 medium and covered by a #1.5 thickness coverslip.

For time-lapse microscopy experiments with the CRISPRi strains (Li et al., 2016), the cells were

induced by adding L-arabinose (0.2%) to liquid cultures after which a sample (~1 µl) was immediately

collected and spotted on an agarose pad containing the appropriate growth medium supplemented

with 0.2% L-arabinose. This was promptly followed by imaging of individual cells. To determine the

1N status of CRISPRi *oriC* cells, we monitored the last division and number of nucleoids based on HU-

mCherry fluorescence. In Figure 1B, the time point "0 min" refers to the time when cells have reached

the 1N status.

For population microscopy experiments with the CRISPRi strains, the cells were induced with

0.2% L-arabinose and allowed to grow in normal conditions until a specific time point (depending on

the growth medium and strain) was reached, after which the cells were spotted on an agarose pad

containing the appropriate growth medium and 0.2% L-arabinose, and imaged (see information for

each experiment in the corresponding Figure). Note that the CRISPRi strains do not metabolize

arabinose due to the *araBAD* deletion.

For the TMT-MS experiments, CRISPRi *oriC* (SJ_XTL676) cells were supplemented with 0.2% L-

arabinose and allowed to grow in liquid M9glyCAAT cultures at 37°C for 0, 120, 180, 240, and 300 min

before harvesting, while CRISPRi *ftsZ* (SJ_XTL229) cells were collected after 0, 60, and 120 min after

arabinose addition. For RNA-seq experiments, CRISPRi *oriC* (SJ_XTL676) cells were supplemented with

0.2% L-arabinose and allowed to grow in liquid M9glyCAAT cultures 37°C for 60, 120 200, and 240 min

before harvesting.

Strains carrying the *dnaC2* mutation were grown at a permissive temperature of 30°C and then

shifted to 37°C to block replication initiation. Transcription inhibition and mRNA depletion were

achieved by exposing cells to 200 µg/ml rifampicin for 30 min before spotting cells on a 1% agarose

pad containing the appropriate M9 medium and rifampicin concentration. The HaloTag was labeled

with Janelia Fluor 549 (JF549) ligand (Grimm et al., 2015) as described previously (Banaz et al., 2019).

Briefly, cells were incubated with 2.5 µM of the JF549 ligand for 30 min while shaking, washed 5 times

with growth medium, and allowed to recover for several generations (while remaining in exponential

phase) prior to imaging.

C. crescentus strains were grown at 22˚C in PYE (2 g/L bacto-peptone, 1 g/L yeast extract, 1

mM $MgSO_4$, 0.5 mM $CaCl_2$) supplemented with 0.03% xylose to induce production of the essential

protein FtsZ (Wang et al., 2001) or DnaA (Gorbatyuk and Marczynski, 2001). For microscopy, cells

were grown in overnight cultures, then diluted at least 1:10,000 in fresh medium and grown to

exponential phase (OD_{660} nm < 0.3). To induce cell filamentation by depleting FtsZ or DnaA, xylose

was removed from the medium by pelleting cells, washing twice with PYE, and resuspending in fresh

PYE. Cultures were then allowed to grow for an additional 30 min to allow ongoing cell division cycles

to complete before spotting on 1% agarose pads containing PYE but lacking xylose to deplete FtsZ or

DnaA. To estimate the concentration of fluorescently-labeled ribosomes and RNAPs by fluorescence

microscopy, cultures were sampled at 0, 4, 8, and sometimes 12 h following xylose depletion with 30

min outgrowth to allow late predivisional cells time to divide before spotting. For timelapse

microscopy, new pads were spotted with cells from the original culture at 0, 4, 8, and sometimes 12

h following xylose removal with 30 min outgrowth in a liquid PYE medium.

Epifluorescence microscopy

For *E. coli*, phase contrast and fluorescence imaging (except for the RpoC-HaloTag-JF549

epifluorescence experiment), were performed on a Nikon Ti2 microscope equipped with a Perfect

Focus System, a 100x Plan Apo λ 1.45 NA oil immersion objective, a motorized stage, a Prime BSI

sCMOS camera (Photometrics), and a temperature chamber (Okolabs). Fluorescence emission was

collected during a 100 or 200 ms exposure time provided by a Spectra III Light Engine LED excitation

source (Lumencor): mCherry – 594 nm excitation, DAPI/FITC/TxRed filter cube (polychroic FF-

409/493/596-Di02, triple-pass emitter FF-1-432/523/702-25); GFP and SYTO RNASelect – 488 nm

excitation, DAPI/FITC/TxRed polychroic filter cube, and an ET525/50M emission filter; YFP – 514 nm

excitation, CFP/YFP/mCherry filter cube (polychroic FF-459/526/596-Di01, triple-pass emitter FF-1-

475/543/702-25), and a FF02-525/40-25 emission filter. The microscope was controlled using NIS-

Elements AR. For time-lapse imaging, phase images were collected every 5 min.

Epifluorescence snapshots of RpoC-HaloTag-JF549 were taken using a Nikon Ti microscope,

equipped with a Perfect Focus System, a 100x Plan Apo λ 1.45 NA oil immersion objective, a motorized

stage and an ORCA Flash 4.0 camera (Hamamatsu). Fluorescence emission was collected during a 200

ms exposure time provided by a Sola solid state white light source (Lumencor) and a Cy3 filter cube

(excitation AT545/25x, dichroic T565lpxr, emission ET605/70m). The microscope was controlled using

NIS-Elements AR. The same microscope and filters were used to capture the EUB338-Cy3 fluorescence,

but using a 100-ms exposure time. The same microscope, with a DAPI filter cube (excitation ET395/25x,

dichroic T425lpxr, emission ET460/50m) and 500-ms exposure time, was used to capture the DAPI

fluorescence in fixed 1N and multi-N cells.

For *C. crescentus*, phase contrast and fluorescence imaging were performed on a Nikon Ti-E

microscope equipped with a Perfect Focus System, a 100x Plan Apo λ 1.45 NA oil immersion objective,

a motorized stage, an Orca-Flash4.0 V2 142 CMOS camera (Hamamatsu) at room temperature.

Chroma filter sets were used to acquire fluorescence images: CFP (excitation ET436/20x, dichroic

T455lp, emission ET480/40m) and mCherry (excitation ET560/40x, dichroic T585lpxr, emission

ET630/75m). The microscope was controlled using NIS-Elements AR. For time-lapse imaging, phase

images were collected every 2.5 min.

Photoactivated localization microscopy

For single-molecule photoactivated localization (PALM) microscopy, coverslips were plasma-cleaned

of background fluorescent particles using a plasma cleaner (PDC-32G, Harrick Plasma). Live cell PALM

microscopy was performed on a Nikon N-STORM microscope equipped with a Perfect Focus System

and a motorized stage. JF549 fluorescence was measured using an iXon3 DU 897 EMCCD camera

(Andor) and excited from a 50 mW 561 nm laser (MLC400B laser unit, Agilent) with 50% transmission.

The laser was focused through a 100x Apo TIRF 1.49 NA oil immersion objective (Nikon) onto the

sample using an angle for highly inclined thin illumination to reduce background fluorescence

(Tokunaga et al., 2008). Fluorescence emission was filtered by a C-N Storm 405/488/561/647 laser

quad set. Transmission illumination was used to gather brightfield images. PALM movies of 20,000

frames were acquired with continuous laser illumination and a camera frame rate of 10.7 ms.

SYTO RNASelect staining experiments

In order to compare the mRNA concentration between 1N and multi-N cells, exponentially growing CJW7576 (CRISPRi *ftsZ*) and CJW7457 (CRISPRi *oriC*) cells were stained with the fluorogenic SYTO RNASelect dye (Invitrogen™, S7576) after CRISPRi induction with 0.2% L-arabinose. To ensure overlapping cell area distributions in the absence of cell division, considering the measured growth rate differences between the 1N and multi-N cells, CRISPRi *oriC* was induced for 3.5 to 4 h whereas CRISPRi *ftsZ* was induced for 1.5 to 2 h. Then, the two populations were mixed at equal optical densities (OD$_{600}$) and stained with 0.5 µM SYTO RNASelect for 15 min at 37°C with shaking. For each staining, a fresh 5µM SYTO RNASelect stock was prepared in L-arabinose-containing medium. Stained cells (~0.5 µL) were spotted on a 1% agarose pad prepared with the same growth medium with L-arabinose for imaging. Five biological replicates were performed.

RpoC-HaloTag-JF549 staining experiments for epifluorescence snapshots

For Figure 4 – supplement 5, CRISPRi *oriC* in CJW7520 cells was induced for 3.5 h whereas CRISPRi *ftsZ* (CJW7527) was induced for 1.5 h with 0.2% L-arabinose to obtain a similar range of cell sizes for imaging. Then the two populations were mixed at equal optical densities (OD$_{600}$) and stained with 2.5 µM JF549 at 37°C for 30 min with shaking. The mixed cells were then washed three times with L-arabinose-containing (0.2%) medium. All washes were performed at 4°C, using ice-cold medium to block cell growth and avoid dilution of the dye. Then, the cells (~0.5 µL) were spotted on a 1% agarose pad prepared with the same L-arabinose-containing growth medium for imaging. Two biological replicates were performed.

Fluorescence *in situ* hybridization experiments

FISH with the EUB338 DNA probe (Amann et al., 1990) was used to compare the concentration of 16S

rRNAs in fixed *E. coli* 1N (SJ_XTL676) versus multi-N (SJ_XTL229) cells, or between fast (M9glyCAAT)

and slow (M9gly) growing wildtype MG1655 populations. Similar to the SYTO RNASelect experiments,

CRISPRi *oriC* was induced for 3.5 to 4 h whereas CRISPRi *ftsZ* was induced for 1.5 to 2 h to ensure

overlapping cell area distributions between 1N and multi-N cells considering the measured growth

rate differences between the two strains. Then, the two populations were mixed at equal optical

densities (OD_{600}) and fixed prior to staining using previously described protocols (Kim et al., 2019; Kim

and Jacobs-Wagner, 2018; Kim and Vaidya, 2020). Note that wildtype cells growing exponentially in

different media (M9gly or M9glyCAAT) were fixed and stained separately (separate tubes and

coverslips but using the exact same washing, pre-hybridization and hybridization buffers).

Pre-hybridization was performed for 2 h at 37°C using a solution that contained 40%

formamide, 2x saline-sodium citrate (SSC), 1x vanadyl ribonucleoside complex (VRC) and 0.4% (w/v)

bovine serum albumin (BSA). Staining was performed for 13 h at 37°C using a solution that contained

500nM EUB338-Cy3 Eubacterial probe (Millipore Sigma, MBD0033), 40% formamide, 2x SSC, 1x VRC,

0.4% (w/v) BSA, 0.4mg/mL *E. coli* tRNA, and 10% dextran sulfate. The high probe concentration

allowed for the saturation of the 16S rRNA as previously shown (Hoshino et al., 2008), which made it

possible to compare rRNA concentrations between different strains and media. After staining, the

fixed cells were washed five times with a wash solution (50% formamide, 2X SSC) and ten times with

1X phosphate-buffered saline (PBS). Right before mounting the coverslip on the glass slide for imaging,

the 1N/multi-N cells were further stained with 1 µg/mL DAPI.

Image processing and data analysis

Data analysis was done in MATLAB (Mathworks) (MAIN_pop_analysis.m script for epifluorescence

snapshots, MAIN_timelapse.m script for timelapse movies, and MAIN_mol_tracking.m script for

single-molecule tracking experiments), except for segmentation of phase contrast images, which was

done in Python (segmentationRun.py) using a convolutional neural network, the Nested-Unet (Wiktor

et al., 2021; Zhou et al., 2020), and the analysis of the SYTO RNASelect and RpoC-HaloTag-JF549

epifluorescence (snapshots_analysis_UNET_version_ND2.py class) that was also performed in Python

3.9 (DNA_limitation_python_environment.yml). The Nested-Unet network was trained for our

microscopy setup using PyTorch 1.7.0 and NumPY 1.19.2 (trainerWrapper.py) (Harris et al., 2020;

Paszke et al., 2019).

Cell area masks from segmentation were linked between time-lapse frames based on

maximum overlap (trackCells.m). Two masks linked to the same cell area were considered a cell

division event. To estimate the absolute growth rate, the cell area over time was smoothed by a

sliding-average window of five data points (time interval 5 min) and the difference in the cell area

between consecutive frames was calculated. The relative growth rate was calculated by dividing the

absolute growth rate by the cell area. Cell areas were converted into volumes using Oufti's scripts

(Paintdakhi et al., 2016). To avoid bias from cells reaching sizes too large to support growth, the time-

lapse data for filamenting cells was truncated based on their maximum absolute growth rate.

Fluorescent ParB-mCherry spots were detected by fitting a 2D Gaussian function to raw image

data (detectSpots.m). First, the fluorescent image was filtered using a bandpass filter to identify the

local maxima. Next, the local maxima were fitted by a Gaussian function and a spot quality score was

calculated based on spot intensity and quality of a Gaussian fit ($Intensity \cdot quality_{fit} = \sigma_{fit}$). The

spot score threshold was determined by visual inspection of the training data and was set to remove

poor-quality spots from analysis.

The number of HU-mCherry-labeled nucleoid areas was determined using Otsu's thresholding

(multithresh.m) (Otsu, 1979). Minimum and maximum area thresholds for an individual nucleoid were

determined by measuring the number of fluorescent spots of ParB protein fusion in HU-labeled

nucleoid areas of a strain (CJW7517) carrying a *parS* site from plasmid pMT1 at *ori1* (Figure 1 –

supplement 3A). Only cells containing a single nucleoid were considered 1N cells. To measure the

total fluorescence intensity of a cell, the median intensity of the area outside the cell areas was

subtracted from the fluorescence intensity of each pixel of a cell, and the intensity of all pixels was

summed together.

For the SYTO RNASelect, RpoC-HaloTag-JF549, and EUB338 epifluorescence snapshot

experiments (Figure 4 and Figure 4 – supplements 1 and 2), the nucleoid objects were segmented

using the *segment_nucleoids* function in the *snapshots_analysis_UNET_version_ND2.py* class. This

function combines a Laplacian of Gaussian (LoG) filter, an adaptive filter, and a hard threshold to

detect the nucleoid boundaries and distinguish between 1N and multi-N cells in the mixed populations.

The image filters were applied using the scikit-image (Van Der Walt et al., 2014) and NumPy Python

libraries. For the SYTO RNASelect-stained cells, the HU-mCherry fluorescence was used to segment

the nucleoid objects. In the EUB338 FISH experiments, the nucleoids were stained with DAPI. For the

RpoC-HaloTag-JF549-stained cells, the fluorescence of RpoC-HaloTag-JF549 bound to nucleoids was

used to segment the nucleoid objects. The number of segmented nucleoid objects was used to

distinguish between 1N (one nucleoid object) and multi-N (two or more nucleoid objects) cells. The

classification results were curated manually by visual inspection.

The SYTO RNASelect concentration corresponds to the total fluorescence of the fluorogenic

dye within the cell boundaries of the cell mask, divided by the area of the cell mask. Similarly, the

RpoC-HaloTag-JF549 and EUB338 concentrations were calculated in arbitrary units.

To ensure that the SYTO RNASelect, the RpoC-HaloTag-JF549, or the EUB338-Cy3 fluorescence

was compared for the same distributions of cell areas between the 1N and multi-N cells in the mixed

populations, random sampling was performed in each cell area bin using a sample size equal to the

smaller cell number between the 1N and multi-N cells (Figure 4 – supplements 1 and 2B). For example,

if in each cell area bin, there were 100 1N cells and 500 multi-N cells, 100 cells were randomly sampled

from the multi-N population to match the sample size of the 1N population. Bins with less than 25

(for the EUB338 experiments) or 50 (for the RNASelect or the RpoC-HaloTag-JF549 experiments) cells

per population across biological replicates were removed from the analysis. This sampling was

performed one time to compare the distributions of the SYTO RNASelect, EUB338, and RpoC-HaloTag-

JF549 (Figure 4B-C and Figure 4 – supplement 2C-D) concentrations between the 1N and multi-N cells.

However, to estimate the average 1N/multi-N SYTO RNASelect, EUB338 or RpoC-HaloTag-JF549 ratio

during cell growth (Figure 4D and Figure 4 – supplement 2E) multiple samplings (with substitution)

were performed for each biological replicate and cell area bin. This allowed us to use all the data while

still comparing equal numbers of 1N and multi-N cells per biological replicate and cell area bin. Cell

area bins with less than 5 (for the EUB338 experiments) or 10 (for the RNASelect or the RpoC-HaloTag-

JF549 experiments) cells per biological replicate were removed from the analysis. Also here, the

sample size was set by the smallest population size (1N or multi-N population) and the number of

iterations was equal to the difference between the populations multiplied by 10.

Single-molecule tracking analysis

Single-molecule tracking data was analyzed as previously described (Mäkelä and Sherratt, 2020).

Candidate fluorescent spots were detected using band-pass filtering and an intensity threshold for

each frame of the time-lapse sequence. These initial localizations were used as starting positions in

phasor spot detection for high-precision localization (Martens et al., 2018). Individual molecules were

then tracked in each cell area by linking positions to a trajectory if they appeared in consecutive

frames within a distance of 0.8 µm. Cell areas were detected from bright-field images using

MicrobeTracker (Sliusarenko et al., 2011). In the case of multiple localizations within the tracking

radius, these localizations were omitted from the analysis. Tracking allowed for a single frame

disappearance of the molecule within a trajectory due to blinking or missed localization. The mobility

of each molecule was determined by calculating an apparent diffusion coefficient, D_a, from the

stepwise mean-squared displacement (MSD) of the trajectory using:

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$$D_a = \frac{1}{4n\Delta t} \sum_{i=1}^{n} [x(i\Delta t) - x(i\Delta t + \Delta t)]^2 + [y(i\Delta t) - y(i\Delta t + \Delta t)]^2$$

where x(t) and y(t) indicate the coordinates of the molecule at time t, Δt is the frame rate of the

camera, and n is the total number of the steps in the trajectory. Trajectories with less than 9

displacements were omitted due to the higher uncertainty in D_a.

The calculated D_a values are expected to reflect different dynamic states of molecules. To

determine the fraction of molecules in each state, $\log_{10}$ transformed D_a data (Figure 2D) was fitted to

a Gaussian mixture model (GMM) using the expectation-maximization algorithm (Bishop, Christopher,

2006). A mixture of 3 Gaussian distributions with free parameters for mean, SD, and weight of each

state were fitted for different conditions (Figure 2D). Additionally, for 1N cells, single-molecule

tracking data were binned and fitted as a function of cell area (Figure 2D – supplement 3). To

determine the active RNAP or ribosome fraction of a single cell, the GMM was used to determine the

state of each molecule from the measured D_a, and the fraction of molecules in the slowest ("active")

state was calculated. Only cells with at least 50 trajectories were considered in the analysis for more

accurate quantification. The total quantity of active molecules was estimated by multiplying the

measured total fluorescence intensity with the measured active fraction as a function of the cell area.

Sample preparation for liquid chromatography coupled to tandem mass spectrometry (LC-MS/MS)

CRISPRi *oriC* (SJ_XTL676) cells were collected 0, 120, 180, 240, and 300 min after addition of 0.2%

arabinose, while CRISPRi *ftsZ* (SJ_XTL229) cells were collected after 0, 60, and 120 min of induction,

and pelleted. Cell pellets were lysed in 1% SDS at 95°C for 10 min (with vigorous intermittent vortexing

and in the presence of 5 mM β-mercaptoethanol as a reducing agent). Cell lysates were cleared by

centrifugation at 15000 x g for 30 min at 4°C. The lysates were alkylated with 10 mM iodoacetamide

for 15 min at room temperature, and then precipitated with three volumes of a solution containing

50% acetone and 50% ethanol. Precipitated proteins were re-solubilized in 2 M urea, 50 mM Tris-HCl,

pH 8.0, and 150 mM NaCl, and then digested with TPCK-treated trypsin (50:1) overnight at 37°C.

Trifluoroacetic acid was added to the digested peptides at a final concentration of 0.2%. Peptides

were desalted with a Sep-Pak 50 mg C18 column (Waters). The C18 column was conditioned with five

column volumes of 80% acetonitrile and 0.1% acetic acid, and then washed with five column volumes

of 0.1% trifluoroacetic acid. After samples were loaded, the column was washed with five column

volumes of 0.1% acetic acid followed by elution with four column volumes of 80% acetonitrile and

0.1% acetic acid. The elution was dried in a Concentrator at 45°C. Peptides (20 μg) resuspended in a

100-mM triethylammonium bicarbonate solution were labeled using 100 μg of Thermo TMT10plex™

in a reaction volume of 25 μl for 1 h. The labeling reaction was quenched with 8 μL of 5%

hydroxylamine for 15 min. Labeled peptides were pooled, acidified to a pH of ~2 using drops of 10%

trifluoroacetic acid, and desalted again with a Sep-Pak 50 mg C18 column as described above. TMT-

labeled peptides were pre-fractionated using a Pierce™ High pH Reversed-Phase Peptide

Fractionation Kit. Pre-fractionated peptides were dried using a concentrator and re-suspended in 0.1%

formic acid.

LC-MS/MS data acquisition

Pre-fractionated TMT-labeled peptides were analyzed on a Fusion Lumos mass spectrometer (Thermo

Fisher Scientific) equipped with a Thermo EASY-nLC 1200 LC system (Thermo Fisher Scientific).

Peptides were separated by capillary reverse phase chromatography on a 25 cm column (75 μm inner

diameter, packed with 1.6 μm C18 resin, AUR2-25075C18A, Ionopticks). Electrospray ionization

voltage was set to 1550 V. Peptides were introduced into the Fusion Lumos mass spectrometer using

a 180 min stepped linear gradient at a flow rate of 300 nL/min. The steps of the gradient were as

follows: 6–33% buffer B (0.1% (v/v) formic acid in 80% acetonitrile) for 145 min, 33-45% buffer B for

15 min, 40-95% buffer B for 5 min, and 90% buffer B for 5 min. Column temperature was maintained

at 50°C throughout the procedure. Xcalibur software (Thermo Fisher Scientific) was used for the data

acquisition and the instrument was operated in data-dependent mode. Advanced peak detection was

disabled. Survey scans were acquired in the Orbitrap mass analyzer (centroid mode) over the range

of 380 to 1400 m/z with a mass resolution of 120,000 (at m/z 200). For MS1 (the survey scan), the

normalized AGC target (%) was set at 250 and the maximum injection time was set to 100 ms. Selected

ions were fragmented by the Collision Induced Dissociation (CID) method with normalized collision

energies of 34 and the tandem mass spectra were acquired in the ion trap mass analyzer with the

scan rate set to "Rapid". The isolation window was set to 0.7 m/z. For MS2 (the peptide fragmentation

scan), the normalized AGC target (%) and the maximum injection time were set to "standard" and 35

ms, respectively. Repeated sequencing of peptides was kept to a minimum by dynamic exclusion of

the sequenced peptides for 30 s. The maximum duty cycle length was set to 3 s. Relative changes in

peptide concentration were determined at the level of the MS3 (reporter ion fragmentation scan) by

isolating and fragmenting the five most dominant MS2 ion peaks.

Spectral searches

All raw files were searched using the Andromeda engine (Thomason, Costantino, and Court 2007)

embedded in MaxQuant (v2.3.1.0) (Cox and Mann, 2008). A Reporter ion MS3 search was conducted

using 10plex TMT isobaric labels. Variable modifications included oxidation (M) and protein N-

terminal acetylation. Carbamidomethylation of cysteines was a fixed modification. The number of

modifications per peptide was capped at five. Digestion was set to tryptic (proline-blocked). Database

search was conducted using the UniProt proteome Ecoli_UP000000625_83333. The minimum

peptide length was seven amino acids. The false discovery rate was determined using a reverse decoy

proteome (Elias and Gygi, 2007).

Proteomics data analysis

Normalization and protein slope calculations were performed as described previously (Lanz et al.,

2022). In brief, the relative signal difference between the TMT channels for each peptide was plotted

against the normalized cell area for each of the bins of *E. coli* cells. For protein detection, we used a

minimum of three unique peptide measurements per protein as a threshold. To derive the protein

slope values shown in Figure 5, individual peptide measurements were consolidated into a protein

level measurement using Python's groupby.median. Peptides with the same amino acid sequence that

were identified as different charge states or in different fractions were considered independent

measurements. We summarized the size scaling behavior of individual proteins as a slope value

derived from a regression. Each protein slope value was based on the behavior of all detected

peptides.

For a given protein, we calculated the cell size-dependent slope as follows:

y_i = relative signal in the ith TMT channel (median of all corresponding peptides in this channel)

x_i = normalized cell size in the ith TMT channel (cell area for a given timepoint / mean cell area for the

experiment)

The protein slope value was determined from a linear fit to the log-transformed data using the

equation:

$$Log_2(y) = Slope \cdot Log_2(x)$$

Variables were log-transformed so that a slope of 1 corresponds to an increase in protein

concentration that is proportional to the increase in cell volume, and a slope of -1 corresponds to

1/volume dilution. Pearson correlation coefficients and p values were calculated using SciPy's

pearsonr module in Python (Virtanen et al., 2020). The results were reproducible across the two

replicates (Figure 5 – figure supplement 1).

Estimation of protein abundance using summed ion intensity

MS1-level peptide ion intensities from experiment #1 were used to estimate the relative protein

abundance. For each protein, all peptide intensities were summed together using the "Intensity"

column of MaxQuant's evidence.txt file. To adjust for the fact that larger proteins produce more

tryptic peptides, the summed ion intensity for each protein was divided by its amino acid sequence

length.

Calculation of distance from *oriC*

Gene coordinates were downloaded from EcoCyc database. The midpoint of each coding sequence

was used to determine the circular distance (in base pairs) from *oriC* (base pair 3925859 of the total

length of 4641652). A script was written to make three distance calculations. First, the direct distance

(the midpoint of each gene minus 3,925,859 bp (*oriC*)) was determined. Next, the midpoint coordinate

of each gene was subtracted by the total genome length (4,641,652 bp) and then subtracted again by

the coordinate of *oriC* (3,925,859 bp). Finally, the midpoint coordinate of each gene was added to the

total genome length (4,641,652 bp) and then subtracted by the coordinate of *oriC* (3,925,859 bp). The

absolute values of these three calculations were then taken and the minimal values represent the

circular distances between *oriC* and each gene.

Sample preparation for RNA-seq experiments

CRISPRi *oriC* strain (SJ_XTL676) was grown in M9glyCAAT at 37°C and cells were collected 60, 120, 200,

and 240 min after addition of 0.2% L-arabinose. Images of cells were acquired at each timepoint to

determine cell area, as described above. For each timepoint, the aliquot was spun down, the

supernatant was removed, and the pellet was flash-frozen. *E. coli* pellets were resuspended in ice cold

PBS and mixed with *C. crescentus* cells in approximately a 1-to-1 ratio based on OD_{600}. *C. crescentus*

cells were originally included with the intent of using them as a spike-in reference. However, the

fraction of final reads obtained from *C. crescentus* transcripts was inconsistent with the initial mixing

ratios. In addition, without knowing the exact DNA concentration in each 1N-rich cell sample, this

spike-in became purposeless and thus was ignored for analysis. Cells (50 μL) in PBS were mixed with

250 μl TRI Reagent (Zymo Research) and lysed by bead beating on a Fastprep 24 (MPbio). Cell debris

were pelleted (14k rpm, 2 min) and the supernatant was recovered. RNA was then extracted using

the direct-zol RNA microprep kit (Zymo Research). Ribosomal RNA (rRNA) was then depleted using

the NEBNext rRNA Depletion Kit for Bacteria (NEB, #E7850) and NEBNext Ultra II Directional RNA

Library Prep Kit for Illumina (NEB, #E7760) was then used to prepare libraries for paired-end (2x150bp)

Illumina sequencing (Novogene).

RNA-seq data analysis

A combined genome file of *E. coli* K-12 MG1655 and *C. crescentus* NA1000 with gene annotations was

generated using a previously described approach (Swaffer et al., 2023). Read mapping statistics and

genome browser tracks were generated using custom Python scripts. For quantification purposes,

reads were aligned as 2x50mers in transcriptome space against an index generated from the

combined gene annotation model using Bowtie (version 1.0.1 ; settings: -e 200 -a -X 1000) (Langmead

et al., 2009). Alignments were then quantified using eXpress (version 1.5.1) (Roberts and Pachter,

2013) as transcripts per million (TPM). TPM values were then recalculated after filtering for only *E.*

coli genes. with TPM values below 1 were then removed from analysis.

The RNA slope (i.e., relative transcript concentration vs. cell area) was calculated for each gene

as follows. TPM values were normalized to the mean of all values for that gene and then log2

transformed. The same normalization was applied to the cell area measurements for each condition.

A linear model was fitted to the normalized log2 data and the slope of the linear regression was taken

as the RNA slope.

Estimation of the minimum genome dilution that limits transcription per nutrient condition

The cell area at which the total active RNAPs deviates from the wildtype scaling behavior was

estimated to approximate the minimal genome dilution required to limit bulk transcription in cells

growing in different media. Deviation in scaling behavior was found to occur at ~2 μm^2 during fast

growth (M9glyCAAT, Figure 3H) or at ~1 μm^2 during slow growth (M9gly or M9ala, Figure 6A-B). Given

such deviations in scaling behavior were observed in cells with a single chromosome copy (i.e., in 1N

cells), the minimal limiting concentration is estimated to be, on average, 0.5 chromosome copies per

μm^2 in M9glyCAAT or 1 chromosome copy per μm^2 in M9gly or M9ala. Based on estimates described

in Appendix 1 (Appendix 1 – Table 1), the average chromosome concentration in wildtype cells is 0.85

chromosome copies per μm^2 for M9glyCAAT, 1.09 chromosome copies per μm^2 for M9gly, and 1.01

chromosome copies per μm^2 for M9ala. This suggests that the genome is already limiting or close to

be limiting (within a few percents) in cells growing in M9gly and M9ala while its concentration is ~40%

above the limiting concentration in cells growing M9glyCAAT.

Mathematical model and simulations

Phenomenological model: We developed a phenomenological model to illustrate cell growth

dynamics. In our models, the number of mRNAs (X) and the number of proteins (Y) in the cell are

described by the differential equations:

$$\frac{dX}{dt} = r_1 \alpha_{RNAP}(X,Y)Y - \delta X \qquad \text{(Eq.1)}$$

$$\frac{dY}{dt} = r_2 \alpha_{ribo}(X,Y)Y \qquad \text{(Eq. 2)}$$

In this model, the parameters r_1 and r_2 are coefficients defined as

$r_1 = \text{\# of mRNAs synthesized per minute} \times \dfrac{\text{\# of RNAPs on mRNA synthesis}}{\text{\# of RNAPs on total RNA synthesis}} \dfrac{\text{\# of RNAPs in cell}}{\text{\# of proteins in cell}}$

$r_2 = \text{\# of protein synthesized per minute} \times \dfrac{\text{\# of ribosomes in cell}}{\text{\# of proteins in cell}}$

Here, $\alpha_{RNAP}(X,Y)$ is the fraction of active RNA polymerases, $\alpha_{ribo}(X,Y)$ is the fraction of active

ribosomes, and δ is the mRNA degradation rate. We assumed that the protein degradation is

negligible because most bacterial proteins are stable (Balakrishnan et al., 2022; Lin and Amir, 2018).

For the fraction of active RNAPs, we considered two different models (models A and B). In model A,

the fraction of active RNAPs was modeled by $\alpha_{RNAP} = \frac{[Z]}{K_1+[Z]}$. In model B, where we included different

states of RNAP and promoter, the expression of α_{RNAP} is more complicated and is described in

Appendix 3. Instead of considering a type of Michaelis-Menten (MM) reaction (Klumpp and Hwa,

2008), model B is based on the mass action law. For both models A and B, the ribosomes were

modeled by $\alpha_{ribo} = \frac{[X]}{K_2+[X]}$. We used $[Z]$ and $[X]$ to represent the genome and mRNA concentrations,

respectively. We assumed that the cell volume (V) and cell area (A) are proportional to the protein

number Y, which is a good approximation (Basan et al., 2015; Kubitschek et al., 1984). While this

assumption has not been verified in 1N cells, the concentration of ribosomes, which constitute most

of the protein mass, were found to remain constant in these cells (Figure 2A). Namely, in our model,

$V = cY$ and $A = c'Y$ with constants c, c'. Under balanced growth conditions, $[Z]$ was assumed to be

constant. For the DNA-limited growth condition (as in 1N cells), we assumed that the genome does

not duplicate and is kept at a single copy per cell ($Z(t) = 1$) while the cell volume continue to increase.

The details for parameters used in this model are described in Table 1.

Numerical simulations: To simulate the model for balanced and DNA-limited growths, we first

fixed a parameter set based on the literature (see Tables 1 and 2) and simulated Eq. 1 and Eq. 2 to

reach the regime of balanced growth. Under balanced growth, we obtained the balanced growth

vector (X^*, Y^*) where Y^* matches the initial protein number reported in the literature (see Table 2).

Then, using the balanced growth vector as the initial condition, we simulated the balanced growth

and DNA-limited growth using different assumptions of genome content $Z(t)$ (described in the

previous paragraph). The simulation was performed using the MATLAB built-in function *ode23* with

relative and absolute errors of the numerical values to be 10^{-4} and 10^{-5}, respectively. For each growth

condition, we obtained growth trajectories $(X(t), Y(t))$, and from $Y(t)$, we calculated the cell

volume $V(t)$ and area $A(t)$ as described above. For model A, the fraction of active RNAPs was

calculated by $\alpha_{RNAP} = \frac{[Z]}{K_1+[Z]}$, while for model B, it is calculated using a more complicated formula

that takes into account RNAP kinetics (see Appendix 3). For both models, the fraction of active

ribosomes was calculated as $\alpha_{ribo} = \frac{[X]}{K_2 + [X]}$.

Parameter fitting: For either model A or B, we fitted our simulation results to all the

experimental data including growth curves, the fraction of active RNAPs, and the fraction of active

ribosomes for 1N and WT or multi-N cells (six datasets in total); see Appendix 2 for the initial

parameter estimation and Appendix 4 for the optimization procedure details. The optimized

parameter sets (see Table 2) were used for the numerical simulations shown in Figure 5. Note that

the optimized parameter set remained within the realistic range for cellular physiology (see Appendix

4 — figure 1 for comparison between original and optimized parameters).

DATA AVAILABILITY

Microscopy image analysis code is available on the Jacobs-Wagner lab github repository

(https://github.com/JacobsWagnerLab/published/tree/master/Makela_Papagiannakis_2024-Elife).

The TMT-MS and RNA-seq data analysis and processing code is available at

https://github.com/mikechucklanz/Proteome_size_scaling_Ecoli   and

https://github.com/georgimarinov/GeorgiScripts.

For this study, the following TMT-MS and RNA-seq data were generated. Dataset 1 includes

the calculated protein slopes from 1N-rich and multi-N cells, the normalized protein proportions, the

summed ion intensities for each protein as well as the distance of its gene from the origin of

replication (*oriC*) and the GO-term analysis. Dataset 2 includes the calculated mRNA slopes, in

comparison with the average protein slopes from 1N-rich cells. Dataset 3 is an ensemble of the TMT-

MS data, the RNA-seq data, and published datasets of essential genes (Gerdes et al., 2003; Goodall et

al., 2018; Hashimoto et al., 2005) and gene expression-related data (Balakrishnan et al., 2022). All

sequencing data associated with this study have been deposited to the GEO repository with the

GSE261497 accession number. The mass spectrometry proteomics data have been deposited to the

ProteomeXchange Consortium via the PRIDE partner repository with the dataset identifier

PXD050093.

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FIGURE LEGENDS

Figure 1. Growth rate and genome copy number in *E. coli* growing in M9glyCAAT.

(**A**) Illustration of 1N (CRISPRi *oriC*, CJW7457) and multi-N (CRISPRi *ftsZ*, CJW7576) cells with different

numbers of chromosomes along with representative microscopy images at different time points

following CRISPRi induction. Scale bars: 1 μm. (**B**) Plot showing representative single-cell trajectories

of cell area as a function of time for the CRISPRi strains following a block in DNA replication and/or

cell division. (**C**) Plot showing the absolute growth rate as a function of cell area for 1N (32735

datapoints from 1568 cells) and multi-N cells (14006 datapoints from 916 cells) in M9glyCAAT. Lines

and shaded areas denote mean ± SD from three experiments. This also applies to the panels below.

(**D**) Absolute and (**E**) relative growth rate in 1N (32735 datapoints from 1568 cells, CJW7457), multi-N

(14006 datapoints from 916 cells, CJW7576), and *dnaC2* 1N (13933 datapoints from 1043 cells,

CJW7374) cells as a function of cell area in M9glyCAAT. (**F**) Absolute and (**G**) relative growth rate in

1N (13933 datapoints from 1043 cells), 2N (6265 datapoints from 295 cells), and >2N (2116 datapoints

from 95 cells) *dnaC2* (CJW7374) cells as a function of cell area in M9glyCAAT.

1285

Figure 2. Lower ribosome activity explains the reduced growth rate of 1N cells growing in M9glyCAAT. (**A**) RpsB-msfGFP fluorescence concentration in 1N (6542 cells, CJW7478) and multi-N (10537 cells, CJW7564) cells as a function of cell area. Lines and shaded areas denote mean ± SD from three experiments. (**B**) Relative protein concentration of different ribosomal proteins in 1N (SJ_XTL676) and multi-N (SJ_XTL229) cells by TMT-MS. 1N-rich cells were collected 0, 120, 180, 240 and 300 min after addition of 0.2% arabinose, while multi-N cells were collected after 0, 60, and 120 min of induction. Blue and cyan represent two independent experiments. Only proteins with at least four peptide measurements are plotted. (**C**) Apparent diffusion coefficients (D_a) of JF549-labeled RspB-HaloTag in WT (32,410 tracks from 771 cells, CJW7528), 1N (848,367 tracks from 2478 cells, CJW7529) and multi-N cells (107,095 tracks from 1139 cells, CJW7530). Only tracks of length ≥9 displacements are included. 1N cells are color-binned according to their cell area while multi-N cells contain aggregated data for ~2-10 μm^2 cell areas. (**D**) D_a in WT cells fitted by a three-state Gaussian mixture model (GMM): 77 ± 1%, 20 ± 1%, and 3.2 ± 0.5% (±SEM) of the ribosome population, from the slowest moving to the fastest moving (32,410 tracks from 771 cells). (**E**) Example WT and 1N cells where active (red, slow-moving) and inactive (gray, fast-moving) ribosomes are classified according to the GMM. (**F**) Active (slow-moving) ribosome fraction in individual WT (237 cells) and 1N (2453 cells) cells as a function of cell area. Only cells with ≥50 tracks are included. Lines and shaded areas denote mean and 95% confidence interval (CI) of the mean from bootstrapping. (**G**) Same as (F) but for WT (237 cells) and multi-N (683 cells) cells. (**H**) Absolute growth rate of 1N and multi-N cells (Figure 1C) as a function of cell area was overlaid with the total active ribosome amount (calculated from Figure 2A, F, and G). Lines and shaded areas denote mean and 95% CI of the mean from bootstrapping. All microscopy data are from three biological replicates.

1308

Figure 3. RNAP activity is reduced in 1N cells growing in M9glyCAAT. (**A**) RpoC-YFP fluorescence

concentration in 1N (3580 cells, CJW7477) and multi-N (5554 cells, CJW7563) cells as a function of cell

area. Lines and shaded areas denote mean ± SD from three experiments. (**B**) Relative protein

concentration of core RNAP subunits and σ^{70} in 1N-rich (SJ_XTL676) and multi-N (SJ_XTL229) cells by

TMT-MS. 1N-rich cells were collected 0, 120, 180, 240, and 300 min after addition of 0.2% L-arabinose,

while multi-N cells were collected after 0, 60, and 120 min of induction. (**C**) Apparent diffusion

coefficients of JF549-labeled RpoC-HaloTag in WT (91,280 tracks from 1000 cells, CJW7519), 1N

(175884 tracks from 1219 cells, CJW7520) and multi-N cells (186951 tracks from 1040 cells, CJW7527).

Only tracks of length ≥9 displacements are included. 1N cells are binned according to cell area while

multi-N cells contain aggregated data for ~2-15 μm^2 cell areas. (**D**) D_a in WT cells fitted by a 3-state

GMM: 49 ± 4%, 49 ± 4%, and 2 ± 0.1% (± SEM) of the RNAP population, from the slowest moving to

the fastest moving (91,280 tracks from 1,000 cells). (**E**) Example WT and 1N cells where active (red,

slow-moving) and inactive (gray, fast-moving) RNAPs are classified according to the GMM. (**F**) Active

RNAP fraction in individual WT (854 cells) and 1N (1024 cells) cells as a function of cell area. Only cells

with at least 50 tracks are included. Lines and shaded areas denote mean ± 95% CI of the mean from

bootstrapping (3 experiments). (**G**) Same as (F) but for WT (854 cells) and multi-N (924 cells) cells. (**H**)

Total amount of active RNAP in WT, 1N and multi-N cells as a function of cell area (calculated from

Figure 3A, F, and G). Also, shown is a linear fit to multi-N data ($f(x) = 4.16 \cdot 10^4 \cdot x$, R^2 0.98). Lines

and shaded areas denote mean and 95% CI of the mean from bootstrapping. All microscopy data are

from three biological replicates.

1329

Figure 4. RNASelect and EUB338 concentration measurements in 1N and multi-N cells. (**A**) Images

of representative cells from a mixed population of 1N (CRISPRi *oriC*) and multi-N (CRISPRi *ftsZ*) cells.

Strains CJW7457 and CJW7576 carrying HU-mCherry were used for the SYTO RNASelect staining

experiment, whereas DAPI-stained strains SJ_XTL676 and SJ_XTL229 were used for the EUB338 rRNA

FISH experiment. (**B**) Concentration distribution of SYTO RNASelect (3077 cells for each population

from five biological replicates) and EUB338 (1254 cells for each population from three biological

replicates) in 1N and multi-N cells. (**C**) The average 1N/multi-N SYTO RNASelect and EUB338

concentration ratio (gray bar) calculated from five and three biological replicates (white circles),

respectively. (**D**) RNASelect and EUB338 concentration ratios as functions of cell area (mean ± SD from

five and three biological replicates, respectively). Single exponential decay functions were fitted to

the average ratios (R^2 > 97%) for each indicated reporter. All concentration comparisons or ratio

calculations were performed for equal numbers of 1N and multi-N cells and overlapping cell area

distributions (see Materials and Methods and Figure 4 – supplement 1).

1343

Figure 5. Mathematical modeling of DNA limitation. (**A-C**) Plots comparing simulation results of

model A (solid lines) with experimental data points (dots) and averages (open squares) in the

M9glyCAAT condition. The multi-N and 1N cells are indicated as blue and yellow, respectively: (**A**) The

relation between the absolute growth rate ($\frac{dA}{dt}$) and cell area (A). (**B**) The relation between the active

RNAP fraction and cell area. (**C**) The relation between the active ribosome fraction and cell area. (**D**)

Diagram showing how the fractions of active RNAPs and ribosomes change with DNA concentration

(colored from yellow to blue). Simulated results (filled dots) are based on model A. Experimental data

(points with 2D error bars) from multi-N and 1N cells were combined and shown in the same plot. (**E**)

Plot showing the effect of DNA limitation (using the ODE model A) on the decay of DNA concentration,

mRNA concentration, and relative growth rate in 1N cells. Each quantity was normalized to their value

at normal cell size (cell area = 2.5 μm^2).

1355

Figure 6. Scaling of the total active RNAPs, total active ribosomes, and growth rate with cell area

during genome dilution in nutrient-poor media. (A) Plot showing the total amount of active RNAPs

(calculated by multiplying the total amount of RNAPs by the fraction of active RNAPs from Figure 6 –

figure supplement 1A and G) in WT (CJW7339) and 1N (CJW7457) cells grown in M9gly as a function

of cell area. Also shown is a linear fit to WT data ($f(x) = 3.99 \cdot 10^4 \cdot x$, R² 0.90). Shaded areas denote

95% CI of the mean from bootstrapping. All data are from three biological replicates. (**B**) Same as (A)

but for cells grown in M9ala (calculated from Figure 6 – figure supplement 1B and H). The linear fit for

WT data is $f(x) = 3.21 \cdot 10^4 \cdot x$, R² 0.95. (**C**) Plot showing the total active ribosome amount of 1N

and multi-N cells grown in M9gly as a function of cell area. The total amount of active ribosomes was

calculated by multiplying the total amount of ribosomes by the fraction of active ribosomes (from

Figure 6 – figure supplement 2A and G). Also shown is a linear fit to WT data ($f(x) = 2.99 \cdot 10^4 \cdot x$,

R² 0.97). Lines and shaded areas denote mean and 95% CI of the mean from bootstrapping. All data

are from three biological replicates. (**D**) Same as (C) but for cells grown in M9ala (calculated from

Figure 6 – figure supplement 2B and H). Here the linear fit to the WT data is $f(x) = 1.90 \cdot 10^4 \cdot x$, R²

0.99. (**E**) Absolute growth rate in 1N (50352 datapoints from 973 cells) and WT (80269 datapoints

from 12544 cells) cells in M9gly. The linear fit for WT data is $f(x) = 6.50 \cdot 10^{-3} \cdot x$, R² 0.99. (**F**)

Absolute growth rate in 1N (71736 datapoints from 909 cells) and WT (63367 datapoints from 6880

cells) cells in M9ala. The linear fit for WT data is $f(x) = 4.05 \cdot 10^{-3} \cdot x$, R^2 0.97. Lines and shaded

areas denote mean ± SD from three biological replicates.

1375

Figure 7. Proteome and transcriptome remodeling in 1N-rich cells. (**A**) Schematic explaining the

calculation of the protein slopes, which describes the scaling of the relative protein concentration

(concentration of a given protein relative to the proteome) with cell area. (**B**) Plot showing the protein

scaling (average slopes from two reproducible biological replicates, see Figure 7 – supplement 1A-B)

in 1N (x-axis) and multi-N (y-axis) cells across the detected proteome (2360 proteins). The colormap

corresponds to a Gaussian kernel density estimation (KDE). (**C**) Plot showing the first principal

component (PC1, which explains 69% of the total variance considering both 1N-rich and multi-N cells)

used to reduce the dimensionality of the relative protein concentration during cell growth. The x-axis

corresponds to the log-transformed cell area, whereas the marker size shows the cell area increase in

linear scale. (**D**) Correlation between average protein and RNA slopes across 2324 genes. The

colormap corresponds to a KDE. (**E**) Relation between mRNA abundance (transcripts per million 60min

after CRISPRi induction) and RNA slopes in 1N-rich cells. The colormap indicates a KDE (3446 genes in

total). The binned data are also shown (orange markers: mean ± SEM, ~380 genes per bin). The

Spearman correlation (ρ = -0.04) is considered not significant (NS, p-value > 10^{-10}). (**F**) Correlation

between RNA slopes and mRNA degradation rate from a published dataset (Balakrishnan et al., 2022)

across genes. The colormap indicates a KDE (2570 genes with positive mRNA degradation rates and

quantified slopes). The binned data are also shown (orange markers: mean ± SEM, ~280 genes per

bin). A significant negative Spearman correlation (p-value < 10^{-10}) is shown for mRNAs with a

degradation rate above 0.7 min^{-1}. (**G**) RNA-slope comparison between essential and non-essential

genes in *E. coli*. Three different published sets of essential genes were used (Gerdes et al., 2003;

Goodall et al., 2018; Hashimoto et al., 2005). The horizontal white lines indicate the inter-quartile

range of each distribution. Mann-Whitney non-parametric tests justify the significant difference (p-

value < 10^{-10}) between the two gene groups (essential vs. non-essential genes).

1399

1400   **SUPPLEMENTARY FIGURE LEGENDS**

1401   **Figure 1 – figure supplement 1. The relative growth rate of WT (CJW7339) cells in M9glyCAAT grown**

1402   **after placing them on an agarose pad.** The plot includes 61562 data points from 11907 cells. Lines

1403   and shaded areas denote mean ± SD from three biological replicates.

1404

1405   **Figure 1 – figure supplement 2. Characterization of ploidy in CRISPRi *oriC* cells.** Representative

1406   microscopy images of CRISPRi *oriC* cells expressing HU-CFP and ParB-mCherry with *parS* site at *ori1*

1407   (CJW7517) in M9glyCAAT 210 min after addition of 0.2% L-arabinose. Scale bar: 1 μm.

1408

Figure 1 – figure supplement 3. Effects of cell area overestimation on the relative growth rate

calculation. The simulated relative growth rate for increasing cell area considering different levels of

cell area over-estimation (0 to 0.2 μm^2) and a constant relative growth rate of 0.0014 1/min. In the

absence of an area overestimation (0 μm^2), the theoretical relative growth rate remains constant as

the cell area increases, consistent with exponential growth. When a constant overestimated area is

added the relative growth rate scales non-linearly with the cell area. This non-linear increase in the

relative growth rate estimation may be confused with super-exponential growth, but it is in fact the

result of cell area overestimation during cell segmentation in the phase contrast channel.

1417

1418 **Figure 1 – figure supplement 4. Relationship between growth rate and cell area in cell types of**

1419 **different ploidy.** (**A**) Absolute and (**B**) relative growth rate in M9glyCAAT in 1N (32735 datapoints from

1420 1568 cells, CJW7457), multi-N (14006 datapoints from 916 cells, CJW7576), and WT (19495 datapoints

1421 from 7440 cells, CJW7339) cells as a function of cell area. Lines and shaded areas denote mean ± SD

1422 from three biological replicates.

1423

Figure 1 – figure supplement 5. Validation of stable growth under microscope observation and

absolute growth rate determination of ppGpp^0 and Δ*recA* cells. (**A**) Plot showing the absolute growth

rate of 1N (CJW7457) cells grown for 90 min in a liquid M9glyCAAT culture in the presence of 0.2% L-

arabinose and then transferred to an agarose pad and imaged for 2 h (dotted line). The data for 1N

(CJW7457) and multi-N (CJW7576) cells (presented in Figure 1C), which were grown on an agarose

pad for 6 h, are also shown for comparison. Lines and shaded areas denote mean ± SD from two

biological replicates. (**B**) Plot showing the absolute growth rate of ppGpp^0 (CJW7518) and Δ*recA*

(CJW7522) cells. Lines and shaded areas denote mean ± SD from two biological replicates. Also shown

are the data for 1N (CJW7457) and multi-N (CJW7576) cells from Figure 1C.

1433

Figure 1 – figure supplement 6. Characterization of ploidy in *dnaC2* cells. (**A**) Representative

microscopy images of WT (top) and *dnaC2* (bottom) cells expressing HU-mCherry growing under

microscope observation in M9glyCAAT. DNA replication in *dnaC2* cells was blocked by growing cells

at 37°C for 145 min. Arrows indicate *dnaC2* cells with one (1N) or two (2N) nucleoids. Scale bars: 1

μm. (**B**) Graph showing the percentage of *dnaC2* cells (CJW7374) with 1, 2 or >2 nucleoids after growth

at 37°C. Shown are aggregated data from three biological replicates.

1440

Figure 1 – figure supplement 7. Relationships between growth rate and cell volume across cell types

of different ploidy in M9glyCAAT. (**A**) Absolute and (**B**) relative growth rate based on cell volume in

1N (32735 datapoints from 1568 cells, CJW7457), multi-N (14006 datapoints from 916 cells, CJW7576),

and *dnaC2* 1N (13933 datapoints from 1043 cells, CJW7374) cells as a function of cell volume. Lines

and shaded areas denote mean ± SD from three experiments. The growth rates are based on volume

in this figure. (**C**) Absolute and (**D**) relative growth rate in 1N (32735 datapoints from 1568 cells,

CJW7457), multi-N (14006 datapoints from 916 cells, CJW7576), and WT (19495 datapoints from 7440

cells, CJW7339) cells as a function of cell area. (**E**) Absolute growth rate and (**F**) relative growth rate

in 1N (13933 datapoints from 1043 cells), 2N (6265 datapoints from 295 cells), and >2N (2116

datapoints from 95 cells) *dnaC2* (CJW7374) cells as a function of cell area. (**G**) Cell width in WT (59072

datapoints from 7640 cells, CJW7339), 1N (41313 datapoints from 1585 cells, CJW7477), and multi-N

(18489 datapoints from 915 cells, CJW7563) cells as a function of cell area. Lines and shaded areas

denote mean ± SD from 3 biological replicates.

1454

1455 **Figure 1 – figure supplement 8. DNA-dependent growth in *Caulobacter crescentus*.** (**A**) Plot showing

1456 the absolute and (**B**) relative growth rate of 1N (DnaA depletion, strain CJW4823, 87 cells) and multi-

1457 N (FtsZ depletion, strain CJW3673, 181 cells) *C. crescentus* cells as a function of cell area. Lines and

1458 shaded areas denote mean ± SD from three biological replicates. (**C**) Example images of 1N and multi-

1459 N *C. crescentus* cells with ploidy represented by the number of ParB-eCFP foci. Scale bar: 2 μm.

1460

1461 **Figure 2 – figure supplement 1. Diffusive characteristics of labeled ribosomes in rifampicin-treated**

1462 **WT cells. (A)** Plot showing the probability density of apparent diffusion coefficients (D_a) of JF549-

1463 labeled RpsB-HaloTag in WT cells (CJW7528) treated with 200 µg/mL rifampicin for 30 min. Only tracks

1464 of length ≥10 are included. Also shown is D_a fitted by three-state Gaussian mixture model (GMM)

1465 (mean ± SEM). Data are from three biological replicates.

1466

1467 **Figure 2 – figure supplement 2. Diffusive characteristics of labeled ribosomes in 1N cells as a**

1468 **function of cell area.** Plots showing the probability density of apparent diffusion coefficients (D_a) of

1469 JF549-labeled RpsB-HaloTag in 1N cells (CJW7529) in M9glyCAAT at different cell areas. Also shown is

1470 D_a fitted by three-state Gaussian mixture model (GMM). Only tracks of length ≥10 are included. Data

1471 are from three biological replicates.

1472

1473 **Figure 3 – figure supplement 1. Diffusive characteristics of labeled RNAPs in rifampicin-treated cells.**

1474 Plot showing the probability density of apparent diffusion coefficients (D_a) of JF549-labeled RpoC-

1475 HaloTag in CJW7519 cells treated with 200 µg/mL rifampicin for 30 min. Also shown is D_a fitted by

1476 three-state Gaussian mixture model (mean ± SEM). Only tracks of length ≥10 are included. Data are

1477 from three biological replicates.

1478

Figure 3 – figure supplement 2. Determination of the relative Rsd concentration in 1N-rich and

multi-N cells as a function of cell area. Plots showing the relative protein concentration of Rsd in 1N-

rich (SJ_XTL676) and multi-N (SJ_XTL229) cells, as determined by TMT-MS. 1N-rich cells grown in

M9glyCAAT were collected 0, 120, 180, 240 and 300 min, while multi-N cells were collected at 0, 60,

and 120 min after 0.2% L-arabinose induction of CRISPRi. Different shades of gray represent two

independent experiments.

1485

Figure 4 – figure supplement 1. Cell sampling to match cell size distribution in mixed populations of

1N and multi-N cells. (**A**) Cell area distributions from mixed CJW7457 (CRISPRi *oriC*) and CJW7576

(CRISPRi *ftsZ*) populations stained with SYTO RNASelect (aggregated data from five biological

replicates) before and after cell area sampling (cell area bins with less than 50 cells were removed

from the analysis). (**B**) Cell area distributions from mixed SJ_XTL676 (CRISPRi *oriC*) and SJ_XTL229

(CRISPRi *ftsZ*) populations stained with the EUB338 FISH probe (aggregated data from three biological

replicates) before and after cell area sampling (cell area bins with less than 25 cells were removed

from the analysis).

1494

Figure 4 – figure supplement 2. Comparison of RpoC-HaloTag-JF549 labelling between 1N and multi-

N cells. (**A**) Phase contrast (left) and RpoC-HaloTag-JF549 fluorescence (right) images of two

representative cells from a mixed population of 1N (CRISPRi *oriC*, CJW7520) and multi-N (CRISPRi *ftsZ*,

CJW7527) cells. (**B**) Cell area distributions from mixed 1N and multi-N cell populations in which RpoC-

HaloTag was stained with the JF549 dye (aggregated data from two biological replicates) before and

after cell area sampling. (**C**) Distributions of RpoC-HaloTag-JF549 signal concentration for 1N and

multi-N cells (748 cells for each population from two biological replicates). (**D**) Average 1N/multi-N

RpoC-HaloTag-JF549 concentration ratio (gray bar), calculated from two biological replicates (white

circles) after sampling the same number of cells per biological replicate and cell area bin for each

population (panel B). (**E**) Plot showing the concentration ratio of fluorescently labeled RpoC

derivatives between 1N and multi-N cells versus the cell area. Squares show mean ± full range of

RpoC-HaloTag-JF549 signal concentration ratios from two biological replicates, whereas grey circles

indicate the mean signal concentration ratio of RpoC-YFP (from data shown in Figure 3A) for

comparison. A linear regression (red dashed line) was fitted to the average RpoC-HaloTag-JF549 ratios.

A cell area of ~2.8 µm^2 corresponds to a 1N/multi-N RpoC-HaloTag-JF549 concentration ratio equal

to 1.

1511

Figure 4 – figure supplement 3. EUB338 staining comparison between fast (M9glyCAAT) and slow

(M9gly) growing populations. (**A**) Relative cell area and EUB338 concentration distributions from

wildtype MG1655 exponentially growing populations in M9glyCAAT or M9gly. Data from two

biological replicates (rep) are shown (M9glyCAAT rep 1: 5867 cells, M9glyCAAT rep 2: 9728 cells,

M9gly rep 1: 8301 cells, M9gly rep 2: 3766 cells). The iso-contour plots (nine levels above the 25th

density percentile) include data from both biological replicates per nutrient condition. (**B**)

Representative fields of the EUB338 fluorescence in stained fixed cells that were grown in M9glyCAAT

(top) or M9gly (bottom). For comparison, the two fields of view have the same dimensions, and the

fluorescence is scaled the same.

1521

1522 **Figure 5 – figure supplement 1. Comparison between experimental results from the M9glyCAAT**

1523 **condition and simulation results using model B.** (**A-C**) Plots comparing simulation results of model B

1524 (solid lines) with experimental data (dots) and averages (open squares). The multi-N and 1N cells are

1525 indicated as blue and yellow, respectively: (**A**) The relation between the absolute growth rate ($\frac{dA}{dt}$) and

cell area (A). (**B**) The relation between the active RNAP fraction and cell area. (**C**) The relation between the active ribosome fraction and cell area. (**D**) A two-dimensional diagram showing how the fractions of active RNAPs and ribosomes change with DNA concentration (colored from yellow to blue). Experimental data (with 2D error bars) from multi-N and 1N cells were combined and shown in the same plot.

Figure 5 – figure supplement 2. Model A-based simulations examining the effects of varying the rates in either mRNA synthesis or mRNA degradation on the relative growth rate of 1N cells as a function of cell area. (**A**) Plot showing the decay of DNA concentration (black) and of the relative growth rate (blue) in 1N cells when the rate of bulk mRNA synthesis (r_1) increases or decreases by ten-fold. Each quantity was normalized to its value at normal cell size (cell area = 2.5 μm^2). (**B**) Same as (A) except mRNA degradation rate δ increasing or decreasing by ten-fold.

Figure 6 – figure supplement 1. Characterization of RNAP diffusion and active fraction in poor media conditions. (**A**) Plot showing the RpoC-YFP fluorescence concentration in 1N (CJW7477) cells grown in M9gly (three experiments) as a function of cell area. Lines and shaded areas denote mean ± SD between biological replicates. (**B**) Same as (A) but for 1N cells grown in M9ala (three experiments). (**C**) Plot showing the probability densities of apparent diffusion coefficients (D$_a$) of JF549-labeled RpoC-HaloTag in WT (CJW7519) and 1N (CJW7520) cells grown in M9gly. Only tracks of length ≥10 are included. 1N cells were binned according to cell area. (**D**) Same as (C) but for cells grown in M9ala. (**E**) Plot showing the probability density of D$_a$ of JF549-labeled RpoC-HaloTag in WT cells (CJW7519) grown in M9gly. Also shown is D$_a$ fitted by three-state Gaussian mixture model (GMM) (mean ± SEM). (**F**)

1548   Same as (E) but for cells grown in M9ala. (**G**) Plots showing the fraction of active RNAPs in individual

1549   WT (CJW7519) and 1N (CJW7520) cells (dots) grown in M9gly as a function of cell area. Only cells with

1550   ≥50 tracks are included. (**H**) Same as (G) but for cells grown in M9ala.

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Figure 6 – figure supplement 2. Characterization of ribosomal diffusion and active fraction in poor

media conditions. (**A**) Plot showing the RpsB-msfGFP fluorescence concentration in 1N (CJW7478)

cells grown in M9gly (from three experiments) as a function of cell area. Lines and shaded areas

denote mean ± SD between the biological replicates. (**B**) Same as (A) but for 1N cells grown in M9ala

(from two experiments). (**C**) Plot showing the probability density of apparent diffusion coefficients (D_a)

of JF549-labeled RpsB-HaloTag across cell areas for WT (CJW7528) and 1N (CJW7529) cells grown in

M9gly. Only tracks of length ≥10 are included. 1N cells were binned according to cell area. (**D**) Same

as (C) for cells grown in M9ala. (**E**) Plot showing probability density of D_a of JF549-labeled RpsB-

HaloTag in WT cells (CJW7528) grown in M9gly. Only tracks of length ≥10 are included. Also shown is

D_a fitted by three-state GMM (mean ± SEM). (**F**) Same as (E) but for cells grown in M9ala. (**G**) Plot

showing the fraction of active ribosomes as a function of cell area for individual WT (CJW7528) and

1N (CJW7529) cells (dots) grown in M9gly. Only cells with ≥50 tracks are included. Shaded areas

denote 95% confidence interval (CI) of the mean from bootstrapping. (**H**) same as (G) but for cells

grown in M9ala.

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1567   **Figure 7 – figure supplement 1. Comparison of protein and mRNA scaling between biological**

1568   **replicates.** (**A**) Correlation of protein slopes across the proteome (2360 proteins) between two

1569   biological replicates for 1N cells. (**B**) Same as (A) but for multi-N cells. (**C**) Correlation of RNA slopes

1570   across the genome (3446 mRNAs) of 1N cells between two biological replicates. The indicated

1571   Spearman correlation shown (ρ) is significant (p-value < 10^{-10}).

1572

Figure 7 – figure supplement 2. Comparison of our data with reference datasets. (A) Comparison

between the concentrations of 3446 RNAs present in both our dataset and that of Balakrishnan et al

(2022). The first time point (60 min) after CRISPRi induction was used to determine the RNA

abundance in our experiments. The RNA concentration was expressed as transcripts per million reads.

The indicated Spearman correlations (ρ) are significant (p-value < 10^{-10}). Each marker represents a

single gene or protein and the colormap shows the KDE. **(B)** Correlations between RNA slopes (from

2577 genes, ~280 genes per bin) in 1N cells and the rate of transcription initiation in wildtype cells

(Balakrishnan et al., 2022). The binned data are also shown (orange markers: mean ± SEM). The p-

value of ρ is not significant (p-value > 10^{-10}). **(C)** Same as (B) but for protein slopes instead of RNA

slopes (2084 genes, ~230 genes per bin). **(D)** Correlation between protein slopes in 1N cells and mRNA

degradation rate in wildtype cells (Balakrishnan et al., 2022). The colormap corresponds to KDE (for

2078 genes with positive mRNA degradation rates). The binned data are also shown (orange markers:

mean ± SEM, ~230 genes per bin). A significant negative Spearman correlation (p-value < 10^{-10}) is

shown for genes with a degradation rate above 0.7 min^{-1}. **(E)** Comparison of the mRNA degradation

rates (Balakrishnan et al., 2022) between essential and non-essential genes in *E. coli*. Three different

published sets of essential genes were used (Gerdes et al., 2003; Goodall et al., 2018; Hashimoto et

al., 2005). The horizontal white lines indicate the inter-quartile range of each distribution. Mann-

Whitney non-parametric tests justify the non-significant difference (p-value > 10^{-2}) between the two

gene groups (essential vs non-essential genes).

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Figure 7 – figure supplement 3. Protein slopes relative to the chromosome position of their gene in

1N-rich and multi-N cells. (**A**) Relationship between the absolute distance of a gene from *oriC* and the

slope of the protein it encodes. Data from 2268 proteins are shown (colormap: Gaussian kernel

density estimation), as well as binned data in six gene distance bins (open circles, average ± SEM, ~370

proteins per bin). For the multi-N cells, the Spearman correlation was not significant (ρ = NS, p-value >

0.01), whereas for the 1N-rich cells, there was a significant Spearman correlation (ρ = 0.23, p-value <

10^{-10}) for genes within 1.35 Mbps of *oriC* (below the mid-point of the 4th gene distance bin). (**B**)

Relationship between the absolute distance of a gene from *oriC* and its mRNA slope. Data from 2200

RNAs are shown (colormap: Gaussian kernel density estimation), as well as binned data in six gene

distance bins (open circles, average ± SEM, ~360 proteins per bin). The Spearman correlation is not

significant (ρ = -0.02, p-value > 0.1).

1604

1605 **Figure 7 – figure supplement 4. Protein slopes relative to protein ion intensity for 1N-rich cells.** The

1606 summed ion intensity of each protein was divided by the protein sequence length and the quotient

1607 was log-transformed. The locations of selected proteins are annotated.

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1614   **Table 1: Model parameter description**

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Para-meter	Biological meaning	Unit	Description
r_1	$\dfrac{\text{bulk transcription rate}}{\text{total protein number}}$	10^{-3}/min	This parameter was estimated as $r_1 = \theta_{RNAP}\beta_{mRNA}/T_{RNAP}$, where θ_{RNAP} is the number of RNAPs normalized by the number of proteins; β_{mRNA} is the fraction of RNAPs engaged in transcription, and T_{RNAP} is the mean mRNA synthesis time.
r_2	$\dfrac{\text{bulk translation rate}}{\text{total protein number}}$	10^{-3}/min	This parameter was estimated by $r_2 = \theta_{ribo}/T_{ribo}$, where θ_{ribo} is the number of ribosomes normalized by the number of proteins, and T_{ribo} is the mean protein synthesis time.
K_1	Saturation level of DNA with respect to RNAP binding	$1/\mu m^3$	This parameter was estimates from $\alpha_{RNAP} = \dfrac{[Z]}{K_1+[Z]}$, where α_{RNAP} is measured in this work and $[Z]_{avg}$, the mean genome copy.
K_2	Saturation level of mRNA with respect to ribosome binding	$1/\mu m^3$	This parameter was estimated as $\alpha_{ribo} = \dfrac{[X]}{K_2+[X]}$, where α_{ribo} is measured in this work and $[X]$, the mRNA concentration.
δ	mRNA degradation rate	1/min	$\delta = 1/\tau_L$, where τ_L is the mRNA lifetime
c	$\dfrac{\text{cell volume}}{\text{protein number}}$	$10^{-6}\mu m^3$	Cell volumes of different culture conditions were measured in this work.
c'	$\dfrac{\text{cell area}}{\text{protein number}}$	$10^{-6}\mu m^2$	Cell area of different culture conditions was measured in this work.
$[Z]_{avg}$	Average genome concentration of normal-growing cells	genome/ μm^3	Estimated by averaging the genome concentration over the cell cycle, see Appendix 1 for details.

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1619   **Table 2: Initial and optimized model parameters**

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Parameter	Unit	Initial estimation	Optimized parameters	
			M9glyCAA (model A)	M9glyCAA (model B)
r_1	10^{-3}/min	1.99	1.22	1.76
r_2	10^{-3}/min	20.0	22.4	22.5
K_1	$1/\mu m^3$	1.40	1.17	1.55
K_2	$1/\mu m^3$	622	797	532

δ	1/min	0.96	1.27	1.31
c	$10^{-6}\mu m^3$	0.28	0.28	0.18
c'	$10^{-6}\mu m^2$	0.47	-	-
X_{ini}	10^2/cell	20.2	-	-
Y_{ini}	10^6/cell	3.82	-	-
$[Z]_{avg}$	genome /cell	1.40	-	-

1621

1622 **Table 3. Strains used in this study**. The abbreviations *kan*, *cat*, and *spec* refer to gene cassette

1623 insertions conferring resistance to kanamycin, chloramphenicol, and spectinomycin, respectively.

1624 These insertions are flanked by Flp site-specific recombination sites (*frt*) that allow the removal of the

1625 insertion using Flp recombinase from plasmid pCP20 (Cherepanov and Wackernagel, 1995).

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Identifier	Genotype	Source
CJW2591	CB15N Δ*bla6 ftsZ*::pBGent-pXyl-ftsZ	BamHI/HindIII fragment was cut from YF1585 and cloned into pBGent. The resulting plasmid was integrated into LS107 (Wang et al., 2001).
CJW3673	CB15N *ftsZ*::pBGentpXyl-ftsZ *parB*::*ecfp-parB*	UV-inactivated φCr30 phage lysate was prepared from CJW2591 and transduced into MT190.
CJW4823	CB15N *parB*::*ecfp-parB dnaA*::Ω xylX::pGM2195	UV-inactivated φCr30 phage lysate was prepared from GM2471. First, pGM2195 was transduced into MT190, followed by a second transduction of Ω into the resulting strain to disrupt the endogenous *dnaA* gene.
CJW6737	DH5α/pKFSS1_parS[pMT1]	parS[pMT1] was amplified from FH3518 (Nielsen et al., 2006) using oligonucleotides NT157 and NT158, digested with BamHI and KpnI, and cloned into the BamHI/KpnI sites of pKFSS1_2 (Takacs et al., 2018).
CJW7019	MG1655 *rpsB*::*rpsB-msfgfp-kan*	(Gray et al., 2019)
CJW7079	CB15N *rplA(L1)*::*rplA(L1)-mCherry*	CJW7080 was subjected to counterselection on 0.3% xylose.

CJW7080	CB15N *rplA(L1)*::pNPTS138-rplA(L1)-mCherry-rplA(L1)DOWN	The vector pNPTS138 (M. R. Alley, unpublished) was PCR-amplified using oligomers JSG_018 and JSG_019. A ~500-bp fragment of the 3' end of the *rplA(L1)* gene, and a ~500 bp fragment immediately downstream of the *rplA* gene (rplA(L1)DOWN), were amplified from a CB15N genome template using oligomers JSG_024 and JSG_025, and JSG_020 and JSG_021, respectively. *mCherry* was amplified from MTLS4218 (Thanbichler et al., 2007) and a linker was introduced using JSG_022 and JSG_023. All products were assembled into a plasmid via Gibson assembly. The resulting plasmid, which was verified by sequencing junctions, was transformed into S17-1 and introduced into CB15N by conjugation with selection for kanamycin and nalidixic acid resistance.
CJW7339	MG1655 *hupA*::*hupA-mCherry-kan*	*hupA*::*hupA-mCherry-kan* from CJW5556 (Paintdakhi et al., 2016) was moved into MG1655 by P1 transduction.
CJW7374	MG1655 *hupA*::*hupA-mCherry* *dnaC*::*dnaC2(ts) mdoB*::*kan*	The kanamycin resistance cassette was excised from CJW7339 by expressing the Flp site-specific recombinase from pCP20 (Cherepanov and Wackernagel, 1995). *dnaC*::*dnaC2(ts) mdoB*::*kan* from FW1957 (Wu et al. 2010) was subsequently moved into this strain by P1 transduction.
CJW7411	MG1655 *glmS1868*::*parS(pMT1)-frt-kanR-frt*	Plasmid backbone was amplified from CJW6919 (Kim et al., 2019) using oligonucleotides AP0039 and AP0040, pMT1 *parS* was amplified from CJW6737 using AP0041 and AP0042, and the fragments were ligated by Gibson assembly. *parS(pMT1)-frt-*

		kanR-frt was amplified from the resulting plasmid with AP0078 and AP0079. The amplicon was inserted between *glmS* and *pstS* by λ-red mediated recombination (Datsenko and Wanner, 2000).
CJW7457	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA hupA*::*hupA-mCherry-kan*	*hupA*::*hupA-mCherry-kan* from CJW5556 (Paintdakhi et al., 2016) was moved into SJ_XTL676 by P1 transduction.
CJW7473	CB15N *rplA(L1)*::*rplA(L1)-mCherry ftsZ*::*pBGentpXyl-ftsZ*	UV-inactivated φCr30 phage lysate was prepared from CJW7080 and used for transduction into CJW3673. Tranductants were selected on kanamycin, and then counterselected on 0.3 % xylose.
CJW7477	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA hupA*::*hupA-mCherry rpoC*::*rpoC-ygfp-kan*	The kanamycin resistance cassette was excised from CJW7457 by expressing the Flp site-specific recombinase from pCP20 (Cherepanov and Wackernagel, 1995). *rpoC*::*rpoC-ygfp-kan* from RLG7470 was subsequently moved into this strain by P1 transduction.
CJW7478	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA hupA*::*hupA-mCherry rpsB*::*rpsB-msfgfp-kan*	The kanamycin resistance cassette was excised from CJW7457 by expressing the Flp site-specific recombinase from pCP20 (Cherepanov and Wackernagel, 1995). *rpsB*::*rpsB-msfgfp-kan* from CJW7019 was subsequently moved into this strain by P1 transduction.
CJW7500	CB15N *rplA(L1)*::*rplA(L1)-mCherry dnaA*::*Ω xylX*::*pGM2195*	UV-inactivated φCr30 phage lysate was prepared from GM2471. A double transduction was performed into CJW7079.
CJW7517	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes*	The strain was generated by first moving *gtrA*::*P58-mCherry-parB(pMT1)-cat* (Wiktor et al., 2021) into SJ_XTL676 by P1 transduction.

	terminator)-(rrnB terminator)>gmpA gtrA::P58-mCherry-parB(pMT1) parS(pMT1) at ori1 hupB::hupB-cfp-kan	Next, *parS(pMT1)-kan* at *ori1* from CJW7411 was moved into the strain by P1 transduction. The resistance genes were excised by expressing the Flp site-specific recombinase from pCP20 (Cherepanov and Wackernagel, 1995). Finally, *hupB::hupB-cfp-kan* from CJW4656 (Gray et al., 2019) was moved into the strain by P1 transduction.
CJW7518	MG1655 *lacY(A177C) araFGH::spec ΔlacI ΔaraE araBAD::dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA hupA::hupA-mcherry ΔrelA251::kan ΔspoT207::cat*	The kanamycin resistance cassette was excised from CJW7457 by expressing the Flp site-specific recombinase from pCP20 (Cherepanov and Wackernagel, 1995). *ΔrelA251::kan* and *ΔspoT207::cat* were subsequently moved into this strain by two P1 transductions from strain CF1693 (Xiao et al., 1991).
CJW7519	MG1655 *rpoC::rpoC-HaloTag-kan*	The strain was generated by first creating *rpoC-HaloTag-kan* amplicon with oligonucleotides JSG_148 and JSG_149 from strain JM41 (Mäkelä and Sherratt, 2020). This amplicon was used to replace the endogenous *rpoC* by λ-red mediated recombination (Datsenko and Wanner, 2000). Finally, *rpoC::rpoC-HaloTag-kan* was moved into MG1655 by P1 transduction.
CJW7520	MG1655 *lacY(A177C) araFGH::spec ΔlacI ΔaraE araBAD::dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA rpoC::rpoC-HaloTag-kan*	*rpoC::rpoC-HaloTag-kan* from CJW7519 was moved into SJ_XTL676 by P1 transduction.
CJW7522	MG1655 *lacY(A177C) araFGH::spec ΔlacI ΔaraE araBAD::dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB*	*recA* was replaced by *kan* using oligonucleotides JSG_173 and JSG_174 in MG1655 by λ-red mediated recombination (Datsenko and Wanner, 2000). The kanamycin resistance cassette was excised from

	terminator)>gmpA hupA::*hupA-mCherry ΔrecA*::*kan*	CJW7457 by expressing the Flp site-specific recombinase from pCP20 (Cherepanov and Wackernagel, 1995) and *ΔrecA*::*kan* was subsequently moved into the strain by P1 transduction.
CJW7527	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(ftsZ)-(S. pyogenes terminator)-(rrnB terminator)>gmpA rpoC*::*rpoC-HaloTag-kan*	*rpoC*::*rpoC-HaloTag-kan* from CJW7519 was moved into SJ_XTL229 by P1 transduction.
CJW7528	MG1655 *rpsB*::*rpsB-HaloTag-kan*	The strain was generated by first creating *rpsB-HaloTag-kan* amplicon with oligonucleotides JSG_157 and JSG_158 from strain JM41 (Mäkelä and Sherratt, 2020). This amplicon was used to replace the endogenous *rpsB* by λ-red mediated recombination (Datsenko and Wanner, 2000). Finally, *rpsB*::*rpsB-HaloTag-kan* was moved into MG1655 by P1 transduction.
CJW7529	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA rpsB*::*rpsB-HaloTag-kan*	*rpsB*::*rpsB-HaloTag-kan* from CJW7528 was moved into SJ_XTL676 by P1 transduction.
CJW7530	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(ftsZ)-(S. pyogenes terminator)-(rrnB terminator)>gmpA rpsB*::*rpsB-HaloTag-kan*	*rpsB*::*rpsB-HaloTag-kan* from CJW7528 was moved into SJ_XTL229 by P1 transduction.
CJW7531	CB15N *rpoC*::*mCherry-rpoC*	Two DNA segments of vector pNPTS138 (M. R. Alley, unpublished) were PCR-amplified using oligomers JSG_134 and JSG_137, and JSG_135 and JSG_136. A ~900 bp fragment

		upstream of the *rpoC* gene and ~900 bp of the 5' end of *rpoC* were amplified from a CB15N genome template using oligomers JSG_128 and JSG_129, and JSG_132 and JSG_133, respectively. *mCherry* was amplified from MTLS#4218 (Thanbichler et al., 2007) and a linker was introduced using oligomers JSG_130 and JSG_131. All products were assembled into a plasmid via Gibson assembly. Proper plasmid assembly was verified by sequencing junctions. Plasmid was transformed into S17-1 and introduced into CB15N by conjugation with selection for kanamycin and nalidixic acid resistance. Second homologous recombination was achieved by counterselection on 0.3 % xylose.
CJW7535	CB15N *rpoC*::*mCherry-rpoC* *dnaA*::Ω xylX::pGM2195	UV-inactivated φCr30 phage lysate was prepared from GM2471. First, pGM2195 was transduced into CJW7531, followed by a second transduction of Ω into the resulting strain to disrupt the endogenous *dnaA* gene.
CJW7563	MG1655 *lacY(A177C)* *araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(ftsZ)-(S. pyogenes terminator)-(rrnB terminator)>gmpA rpoC*::*rpoC-ygfp-kan*	*rpoC*::*rpoC-ygfp-kan* from RLG7470 was moved into SJ_XTL229 by P1 transduction.
CJW7564	MG1655 *lacY(A177C)* *araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(ftsZ)-(S. pyogenes terminator)-(rrnB terminator)>gmpA rpsB*::*rpsB-msfgfp-kan*	*rpsB*::*rpsB-msfgfp-kan* from CJW7019 was moved into SJ_XTL229 by P1 transduction.
CJW7569	CB15N *rpoC*::*mCherry-rpoC* *ftsZ*::pBGentpXyl-ftsZ	UV-inactivated φCr30 phage lysate was prepared from CJW2591 and transduced into CJW7531.

CJW7576	MG1655 *lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(ftsZ)-(S. pyogenes terminator)-(rrnB terminator)>gmpA hupA*::*hupA-mCherry-kan*	*hupA*::*hupA-mCherry-kan* from CJW5556 (Paintdakhi et al., 2016) was moved into SJ_XTL229 by P1 transduction.
GM2471	CB15N *dnaA*::Ω *xylX*::pGM2195	(Gorbatyuk and Marczynski, 2001)
LS107	CB15N Δ*bla6*	(West et al., 2002)
MG1655	*F- lambda- ilvG- rfb-50 rph-1*	(Guyer et al., 1981)
MT190	CB15N *parB*::*ecfp-parB*	(Thanbichler and Shapiro, 2006)
RLG7470	*rpoC*::*rpoC-ygfp-kan*	(Bakshi et al., 2012)
SJ_XTL229	*lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(ftsZ)-(S. pyogenes terminator)-(rrnB terminator)>gmpA*	(Li et al., 2016)
SJ_XTL676	*lacY(A177C) araFGH*::*spec ΔlacI ΔaraE araBAD*::*dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA*	(Si et al., 2017)
YB1585	CB15N *ftsZ*::pBGST18-pXyl-ftsZ	(Wang et al., 2001)

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1629 **Table 4. Oligonucleotides used in this study.**

Name	Sequence
AP0039	ACCCAACTTAATCGCTGTAGGCTGGAGCTGCTTCG
AP0040	ATTAATTGCGTTGCGCAGTTCCCTACTCTCGCATGGG
AP0041	GAGAGTAGGGAACTGCGCAACGCAATTAATGTGAGTTAGC
AP0042	CAGCTCCAGCCTACAGCGATTAAGTTGGGTAACGCCA
AP0078	ATCAAACATCCTGCCAACTCCATGTGACAAACCGTCATCTTCGGCTACTTGCAACGCAATTAATGTGAGTTAGC
AP0079	ACAAACATTAATAACGAAGAGATGACAGAAAAATTTTCATTCTGTGACAGCCCTGATTCCGTGAGGATGC
JSG_018	GCCCGAGGGCACGTGACGCGTCTCCGGATG
JSG_019	ACCTCGGCGATCGCGAACGCCGAAGCTAGCGAATTCGTGGATC
JSG_020	GAATTCGCTAGCTTCGGCGTTCGCGATCGCCGAGGTG

JSG_021	GGCATGGACGAGCTGTACAAGTAAGCCACCCAAGTTTTAGTAAGCG
JSG_022	CGCTTTACTGGGTACGCTTACTAAAACTTGGGTGGCTTACTTGTACAGCTCGTCCATGCC
JSG_023	AACGTTACGCGTCACCGGTCGGCCACCATGGTGAGCAAGGGCGAG
JSG_024	GGCCGACCGGTGACGCGTAACGTTCGAATTGGCGCCGATCGAGCTGATG
JSG_025	CGGAGACGCGTCACGTGCCCTCGGGCACCGGCC
JSG_128	TCCGTAATACGACTCACTTAAGGCCTTGACGATGGTCAAGGTCTTCGTGG
JSG_129	GCCATGTTATCCTCCTCGCCCTTGCTCACCATCTTGGTTCCTTCTGCGGG
JSG_130	TTTTCGCGGGAAACCCCGCAGAAGGAACCAAGATGGTGAGCAAGGGCGAG
JSG_131	TTCAGGACTTCCTGGTTCATGCTGCCGCTGCCGCTGCCCTTGTACAGCTCGTCCATGC
JSG_132	AGCTGTACAAGGGCAGCGGCAGCGGCAGCATGAACCAGGAAGTCCTGAAC
JSG_133	ATGTACAGGCATGCGTCGACCCTCTAAGCATCCGCTTTTCGTTG
JSG_134	CGCAACGAAAAGCGGATGCTTAGAGGGTCGACGCATGC
JSG_135	CACGAAGACCTTGACCATCGTCAAGGCCTTAAGTGAGTCG
JSG_136	TTATCCGTACTCCTGATGATGC
JSG_137	GGGATCGCAGTGGTGAGTAAC
JSG_148	GCCTGGCAGAACTGCTGAACGCAGGTCTGGGCGGTTCTGATAACGAGTAATCGGCTGGCTCCGCTGCT
JSG_149	CATAAAAAAACCCGCCGAAGCGGGTTTTTACGTTATTTGCGGATTAACGAGGATCCCATATGAATATCCTCCTT
JSG_157	GTTCTCAGGATCTGGCTTCCCAGGCGGAAGAAAGCTTCGTAGAAGCTGAGTCGGCTGGCTCCGCTGCT
JSG_158	TTGCCGCCTTTCTGCAACTCGAACTATTTTGGGGGAGTTATCAAGCCTTAGGATCCCATATGAATATCCTCCTT
JSG_173	AAAAAAGCAAAAGGGCCGCAGATGCGACCCTTGTGTATCAAACAAGACGAGTGTAGGCTGGAGCTGCTTC
JSG_174	CAACAGAACATATTGACTATCCGGTATTACCCGGCATGACAGGAGTAAAATGTACAAGAAAGCTGGGTACG
NT157	TATGGATCCTGTTTTTCACCACGCCAATTTCATGG
NT158	TATGGTACCGAGGTTGAAAAGCGTGGTG

1630

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Figure 6

Figure 7

Figure 1 Figure supplement 1

CRISPRi *oriC*

Figure 1 Figure supplement 2

Figure 1 Figure supplement 3

Figure 1 Figure supplement 4

Figure 1 Figure supplement 5

Figure 1 Figure supplement 6

Figure 1 Figure supplement 7

Figure 1 Figure supplement 8

Ribosome, 200 µg/ml rifampicin

527 cells
89508 tracks

Inactive
94.5 ± 0.1%

Free protein
4.5 ± 0.2%

Active
1.1 ± 0.02%

Probability density

$\log_{10}(D_a)$ (µm²/s)

Figure 2 Figure supplement 1

Ribosome CRISPRi *oriC* M9glyCAAT

Figure 2 Figure supplement 2

Figure 3 Figure supplement 1

Figure 3 Figure supplement 2

Figure 4 Figure supplement 1

Figure 4 Figure supplement 2

A

B

Figure 4 Figure supplement 3

Figure 5 Figure supplement 1

Figure 5 Figure supplement 2

Figure 6 Figure supplement 1

Figure 6 Figure supplement 2

Figure 7 Figure supplement 1

Figure 7 Figure supplement 2

Figure 7 Figure supplement 3

Figure 7 Figure supplement 4