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

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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 results in a decrease in the concentration of active RNA polymerases and ribosomes. The resulting sub-linear scaling of total active RNA polymerases and ribosomes with cell size leads to sub-exponential growth, even within physiological cell sizes. Cell growth rate scales proportionally with the total number of active ribosomes in a DNA concentration-dependent manner. Tandem-mass-tag mass spectrometry experiments further reveal that a decrease in DNA-to-cell-volume ratio proportionally remodels the composition of the proteome with cell size independently of the environment. Altogether, our findings indicate that genome concentration is an important driver of exponential cell growth and a global modulator of proteome composition in *E. coli*. Comparison with studies on eukaryotic cells suggests DNA concentration-dependent scaling principles of gene expression across domains of life.

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 mass spectrometry 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 in *E. coli.*

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, producing cells with a single copy of the

chromosome (Figure 1A) (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 (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 (Figure 1A) (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". 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 by the cell area. We chose to use cell area

rather than cell volume for growth rate measurements because cell area is what we measured in our

two-dimensional cell images, and the average cell width remained largely constant for 1N and multi-

N cells following CRISPRi induction (Figure 1 – figure supplement 1A). Furthermore, we found that

absolute and relative growth rates based on extracted cell volumes produced similar results (Figure 1

– figure supplement 1B-K) to those based on cell areas (Figure 1 and Figure 1 – figure supplement 2).

Therefore, we will report growth rate measurements based on cell areas hereafter.

For the CRISPRi *oriC* strain, we selected 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 3A), used

here to determine the number of nucleoids and chromosomal origins per cell. We found that 96 ± 1%

(mean ± standard deviation, SD, n = 3378 cells, three biological replicates) of cells 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. For these cells, the scaling between absolute growth rate and cell size might

even be slightly greater than expected for exponential growth, as the relative growth rate was not

perfectly constant and mildly increased with cell area (Figure 1E). This slight increase would be

consistent with the super-exponential growth pattern previously described for wild-type (WT) cells

(Cylke and Banerjee, 2023; Kar et al., 2021). Multi-N cells grew identically to WT within the same cell

size range (Figure 1 – figure supplement 2). In contrast, 1N cells grew significantly slower than multi-

N-cells and their absolute growth rate only moderately increased with cell area, approaching an

apparent plateau at large cell sizes (Figure 1C-D). This sub-exponential growth resulted in a relative

growth rate that decreased with cell area (Figure 1E). The striking divergence in growth between 1N

and multi-N cells of the same size suggested that growth is dependent on DNA concentration. 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 2), suggesting that growth

rate reduction occurs soon after DNA replication fails to initiate.

We ruled out that the slower growth of 1N cells 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 4). Furthermore, 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 and E).

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 3B

and C), 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.

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).

This difference in DNA concentration explains the lower absolute growth rate of 1N cells relative to

WT even at the smallest cell sizes (Figure 1- figure supplement 2). To examine whether cells are also

subject to DNA-limited growth when multi-fork DNA replication is rare or nonexistent, we measured

growth of 1N cells in two different nutrient-poor media, M9 glycerol (M9gly) and M9 L-alanine (M9ala).

In both conditions, the growth rate scaled slower with cell area in 1N cells relative to WT cells (Figure

1H-K). Here again, this difference in growth was apparent in the cell size range of WT cells, indicating

that the difference in growth rate is not simply the result of a non-physiological regime. Altogether,

our data suggest that in WT cells, the genome concentration is (or is close to be) limiting for growth

and that growth rate scales with ploidy.

152 **The concentration of ribosomal proteins remains relatively constant in DNA-diluted cells.**

153 Ribosome content is often proposed to explain the approximately exponential growth of biomass in

154 bacteria, with growth rate being directly proportional to ribosome concentration (Bremer and Dennis,

155 1996; Ecker and Schaechter, 1963; Scott et al., 2014, 2010). Therefore, we first quantified the

156 fluorescence concentration of a monomeric superfolder green fluorescent protein (msfGFP) fusion to

157 the ribosomal protein RpsB (expressed from the native chromosomal locus) in 1N and multi-N cells in

158 M9glyCAAT as a function of cell area. We found it to be almost identical between the two CRISPRi

159 strains and relatively constant across cell areas, regardless of DNA content (Figure 2A).

160 To exclude the possibility that the msfGFP tag altered the synthesis of RpsB or that this protein

161 behaved differently from other ribosomal proteins, we adapted a tandem-mass-tag (TMT) mass

162 spectrometry (MS) method recently developed to examine cell size-dependent proteome scaling in

163 yeast and human cells (Lanz et al., 2022). Note that for the CRISPRi *oriC* strain, a minority (~10-15%)

164 of cells have more than one nucleoid. These cells were excluded from the analysis of our single-cell

165 microscopy experiments. However, this could not be done for the TMT-MS experiments, which

166 provide population-level measurements. Therefore, for this TMT-MS section, we will refer to the

167 CRISPRi *oriC* cell population as "1N-rich" cells, instead of just "1N" cells. Using the TMT-MS approach,

168 we found that the relative concentration of all (54) high-abundance ribosomal proteins (including

169 untagged RpsB) remained approximately constant across all sizes of 1N-rich cells and was relatively

170 similar between 1N-rich and multi-N cells (Figure 2B). Only the ribosomal protein L31B, a stationary

171 phase paralog of the more prevalent exponential phase ribosomal protein L31A (Lilleorg et al., 2019),

172 displayed significant dilution in 1N cells (Dataset 1). Ribosomal protein concentration also appeared

173 to remain constant in 1N cells in nutrient-poor media based on RpsB-msfGFP fluorescence intensity

measurements in single cells (Figure 2 – figure supplement 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 DNA-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 at the endogenous 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 2). The estimated fraction (~77%) of

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

biochemical studies under these growth conditions (Blundell and Wild, 1971; Mohapatra and

Weisshaar, 2018; Phillips et al., 1969; Sanamrad et al., 2014).

Upon fitting the D_a values of ribosomes in 1N cells of different sizes (Figure 2E), we observed

a significant reduction in the slow-diffusing ribosome population (Figure 2 – figure supplement 3).

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). The reduction in fraction of active ribosomes was less

pronounced in 1N cells growing in M9gly and M9ala (Figure 2 – figure supplement 4), consistent with

the smaller deviation in growth rate between 1N and WT cells (Figure 1H-K).

To estimate the total number of active ribosomes per cell in M9glyCAAT, 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 in M9glyCAAT (Figure 2H),

indicating cell growth rate is directly proportional to the increase in total active ribosomes. We also

estimated the total number of active ribosomes in WT and 1N cells in M9gly and M9ala, where, overall,

we observed similar trends (Figure 2 – figure supplement 4G-H). Altogether, the results are consistent

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

rate.

DNA dilution reduces the activity of RNA polymerases.

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

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

cells, the total activity of RNAPs 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 in M9glyCAAT 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 3B),

clearly demonstrating that the abundance of RNAPs was not the limiting factor. RNAP concentration

also increased, albeit to a lesser degree, in 1N cells in nutrient-poor media based on fluorescence

intensity measurements (Figure 3 – figure supplement 1).

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

live cells in M9glyCAAT 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 corresponded to RNAPs actively engaged

in transcription (Figure 3 – figure supplement 2). 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 in all tested media (Figure 3F-G and Figure 3 – figure

supplements 3 and 4). However, because the RNAP concentration simultaneously increased in 1N

cells, it was 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 active fraction in 1N cells was not the mere result of the increase in RNAP

concentration. Indeed, in M9glyCAAT, 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).

This was also true in M9gly and M9ala (Figure 3 – figure supplement 4G-H). The reduction in the total

amount of active RNAPs was also readily apparent in 1N cells within the range of WT cell sizes (Figure

3H and Figure 3 – figure supplement 4G-H).

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 5), eliminating Rsd as 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

would reduce the pool of mRNAs available for ribosomes.

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 display exponential growth, whereas

if DNA and mRNAs are limiting, cells will adopt linear growth. Our experiments showed that 1N cells

converge toward linear growth (toward slope = 0 in Figure 1C, H, and J), 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 DNA 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, $\alpha_{RNAP}(X,Y)$ is the fraction of active RNAPs,

δ is the mRNA degradation rate, $\alpha_{ribo}(X,Y)$ is the fraction of active ribosomes, and $\frac{dY}{dt}$ corresponds

to the absolute growth rate. For simplicity, we assumed that the 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). For detailed description and estimation of the model parameters, see

Table 1 and Appendix 1.

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

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

proteome does not change (see Materials and Methods). Model B considered RNAP kinetics (with

three different RNAP states: free, promoter-bound, and transcribing) and took into consideration the

experimentally observed increase in RNAP concentration in 1N cells (Figure 3A-B, see Materials and

Methods and Appendix 2). For both models, α_{RNAP} depended on DNA concentration. In 1N cells, the

DNA amount was fixed to 1 genome while it scaled with cell volume in multi-N cells. We then used

both 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). 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 in M9glyCAAT (see Materials

and Methods and Appendix 3).

As shown in Figure 4A-D (model A) and Figure 4 – figure supplement 1 (model B), both models

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

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 4A and Figure 4 – 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 4B-D and Figure 4 – figure supplement 1B-D).

In the absence of published values for the RNAP kinetic constants in nutrient-poor media, we

only used the simpler model A for the M9gly and M9ala conditions. Here again, the model reproduced

the trends for the experimental measurements of WT cells (gray) and 1N cells (yellow) (Figure 4 –

figure supplement 2), with one notable deviation. At cell birth, the curves of fractions of active RNAPs

and ribosomes for 1N cells started slightly higher than the ones for WT cells due to a limitation of our

ODE model, which uses the average concentration of genome and does not include DNA replication

dynamics.

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 (Figure 4E). As mRNAs become limiting, the fraction

of ribosomes engaged in translation decreases. This, in turn, decreases the rate in 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 4E).

Since the models predicted a reduced mRNA pool in 1N cells, we performed live-cell staining

with SYTO RNASelect (Wu et al., 2020), a fluorogenic RNA-specific dye that primarily (~70% of the

signal) binds mRNAs in *E. coli* based on rifampicin treatment (Bakshi et al., 2014). In our RNASelect

staining experiments, we mixed 1N cells with multi-N cells of similar size ranges prior to incubation

with the dye 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 (Figure 4F). Single cells were then sampled to ensure that the cell area distributions

of the two populations perfectly matched (Figure 4 – figure supplement 3). Comparison between the

two sampled populations from five independent experiments 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 4G-H). We also found that the RNASelect concentration ratio between 1N and multi-N cells

decreased exponentially with increasing cell area and thus DNA dilution (Figure 4I), in line with the

model prediction (Figure 4E). Furthermore, both the model (Figure 4E) and our experimental findings

(Figure 4I) suggest that the effects of DNA limitation on the mRNA concentration already appear at

physiological cell area ranges (between 2 and 3 μm^2).

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 staining experiments with the

HaloTag dye JF549 in CRISPRi strains expressing RpoC-HaloTag (Figure 4 – figure supplement 4A-B).

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 4C-E). Hence the RNASelect results are consistent with a reduced mRNA

concentration in 1N cells caused by DNA dilution and reduced global transcription activity.

Genome dilution incrementally changes the composition of the 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. 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 relative concentration of a protein remains constant

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 5A).

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

(Figure 5 – figure supplement 1A-B) but drastically different between 1N-rich cells and multi-N cells

(Figure 5B, Dataset 1). In the control multi-N cells where the genome concentration does not change

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

constant, with their concentrations decreasing or increasing by less than 20% per cell size doubling

(i.e., slopes > -0.2 or < 0.2; Figure 5B and Dataset 1). This indicates 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 that maintained similarly constant concentrations across

cell areas (i.e., slopes > -0.2 or < 0.2) dropped to ~37% (859/2360) (Figure 5B and Dataset 1). A

principal component analysis on the relative protein concentration during cell growth confirmed that

the relative proteome composition changes proportionally with genome dilution (1N-rich cells),

whereas it remains constant when the DNA-to-cell volume is maintained (multi-N cells) (Figure 5C).

Interestingly, for 1N-rich cells, we also observed a slight yet significant positive correlation

(Spearman ρ = 0.23, p-value < 10^{-10}, for genes within 1.35 Mb from *oriC*) between protein slope and

the gene distance from *oriC* (Figure 5D). In other words, genes closer to *oriC* were more likely to

encode proteins that dilute during DNA-limited growth (protein slope < 0) compared to distal genes

(Figure 5D). This was irrespective of their total protein abundance based on summed ion intensities

normalized by protein sequence lengths (Figure 5E). This may suggest the existence of a mechanism

that compensates for the gene dosage associated with DNA replication.

To examine whether the proteome scaling behavior stems from 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, Figure 5 – figure supplement 1C). We also found a strong

correlation in scaling behavior with cell area between mRNAs and proteins across the genome

(Spearman ρ = 0.76, Figure 5F and Dataset 2), indicating that most of the changes in protein levels

observed upon genome dilution take place at the mRNA level.

DISCUSSION

In this study, we show that genome concentration acts as a rate-limiting factor for exponential cellular

growth and a modulator of proteome composition in *E. coli*. These roles for genome concentration

help explain why the timing of DNA replication is so robustly linked to cell volume across

environmental and genetic conditions that affect cell size (Donachie, 1968; Govers et al., 2024; Si et

al., 2017; Zheng et al., 2016).

Our data suggest that DNA limitation in 1N cells affects cell growth rate through modulation

of downstream transcription and translation activities (Figures 2-4 and associated figure supplements).

As a result of growth-induced dilution, the genome becomes increasingly limiting as a template,

decreasing the fraction of active RNAPs (Figure 3). This indicates a sub-linear scaling of global

transcription relative to the cell size. We propose that this reduced transcription activity in

comparison to cells undergoing DNA replication results in a gradual decrease in total mRNA

concentration (Figure 4E-G). Reduced mRNA availability would cause a decrease in the fraction of

ribosomes engaged in translation (Figure 2F and Figure 2 – supplement 4), which would, in turn, lead

to sub-linear scaling of global protein synthesis and absolute growth rate with cell size (Figure 2H and

Figure 2 – supplement 4). It is also possible that the cumulative effect of small changes in proteome

composition in 1N cells contributes to their growth rate defect.

The 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 – supplement 6A and B). In this

organism, filamenting 1N and multi-N cells were generated by depleting the DNA replication initiation

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

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

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

system (Figure 1 –supplement 6C). The fact that DNA limitation for cellular growth was also observed

in *C. crescentus* 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.

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

replication-arrested cells that are still within or close to physiological sizes—results in growth rate

reduction in *E. coli* and *C. crescentus* (Figure 1 and Figure 1 – supplements 2 and 6). Thus, under our

standard growth conditions, cells appear to live at the cusp of DNA limitation for cellular growth. 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 at the cusp of DNA limitation

in bacteria? While *E. coli* carefully controls its DNA 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 some 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).

It will be interesting to explore in future studies 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 DNA 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 as

well. *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 in 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

cultures through the gradual loss of genome copies (Takacs et al., 2022).

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).

In yeast cells, an increase in RNAP II gene occupancy combined with a decrease in mRNA

turnover helps mitigate DNA dilution on global transcription activities up to a certain 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 bacteria, potentially in a growth medium-dependent

manner. For example, in our *E. coli* experiments, we noted that the global transcriptional activity (total

amount of active RNAPs) strongly deviated from proportional scaling with cell size in 1N cells

compared to WT and multi-N cells in all tested medium conditions (Figure 3H and Figure 3 –

supplement 4G-H). This indicates that the genome content limits transcription. However, the global

translation activity (total amount of active ribosomes) only strongly deviated from proportional

scaling with cell sizes in 1N cells growing in the relatively rich medium (M9glyCAAT) condition (Figure

2H). In poor media (M9gly and M9ala), the deviation was far less pronounced (Figure 2H and Figure 2

– supplement 4G-H), suggesting that a decrease in mRNA turnover and/or an increase in ribosome

occupancy per transcript partially buffer(s) DNA limitation on transcription in poor media.

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

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

concentration in controlling protein expression.

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 behavior (Figure 5 – supplement 2). What determines the

scaling behavior of proteins is not clear. We found that, in *E. coli*, the alteration in proteome

composition largely occurs at the mRNA level (Figure 5F) and partially involves chromosomal

positioning (Figure 5D).

Finally, 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 5). 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.

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 RNAseq experiments, CRISPRi *oriC* (SJ_XTL676) cells were supplemented with

0.2% L-arabinose and allowed to grow 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 onto 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, an ORCA Flash 4.0 camera (Hamamatsu) and a temperature chamber (Okolabs). 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, dicrhoic T565lpxr, emission ET605/70m). The

microscope was controlled using NIS-Elements AR.

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^{TM}, 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 was induced for 3.5 h whereas

CRISPRi *ftsZ* was induced for 1.5 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 the 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.

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. We

confirmed that the relative reduction in the growth rate of 1N in comparison to multi-N cells was not

due to longer time-lapse duration as we observed no differences when acquiring shorter 2 h time-

lapse sequences (Figure 1 – figure supplement 5A). Finally, we confirmed that cells were under stable

growth conditions prior to starting imaging by showing that relative growth remained constant from

the beginning of acquisition (Figure 1 – figure supplement 5B).

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 * $quality_{fit}$ / σ_{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 were detected 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 fluorescent intensity of each pixel of a cell, and the intensity of all pixels was

summed together.

For the SYTO RNASelect and RpoC-HaloTag-JF549 epi-fluorescence snapshot experiments

(Figure 4F-I, Figure 4 – supplement 4 and Figure 4 – supplement 5), 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 (Harris et al., 2020) Python libraries. For the SYTO RNASelect-stained cells, the HU-

mCherry fluorescence was used to segment the nucleoid objects. For the RpoC-HaloTag-JF549-stained

cells, the fluorescence of RpoC-HaloTag-JF549 bound to nucleoids was used to segment the nucleoid

objects.

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 concentration was calculated in arbitrary units.

To ensure that the SYTO RNASelect or the RpoC-HaloTag-JF549 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 4 and 5B). For example, if in each

cell area bin, there were 200 1N cells and 100 multi-N cells, 100 cells were randomly sampled from

the 1N population to match the sample size of the multi-N population. Bins with less than 50 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 (Figure 4G) and RpoC-HaloTag-JF549

(Figure 4 – supplement 5C) concentrations between the 1N and multi-N cells. However, to estimate

the average 1N/multi-N SYTO RNASelect or RpoC-HaloTag-JF549 ratio during cell growth (Figure 4I

and Figure 4 – supplement 5E) 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

10 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:

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

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 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:

771             $Log_2(y) = Slope*log_2(x)$

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

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

774   1/volume dilution. Pearson correlation coefficients and p values were calculated using SciPy's

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

776   replicates (Figure 5 – figure supplement 1).

Estimation of protein abundance using summed ion intensity

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

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

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

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

784 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 3,925,859 of the total

length of 4,641,652). 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

phosphate buffer saline solution (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 TPM (Transcripts Per Million). TPM values were then recalculated after filtering for only *E.*

coli genes. 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.

Mathematical model and simulations

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

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

described by the differential equations:

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

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

where $r_1 = \frac{\text{bulk transcription rate}}{\text{total protein number}}$, $r_2 = \frac{\text{bulk translation rate}}{\text{total protein number}}$, $\alpha_{RNAP}(X,Y)$ 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 2. For both models, 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 take into account RNAP kinetics (see Appendix 2). 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 1 for the initial

parameter estimation and Appendix 3 for the optimization procedure details. The optimized

parameter sets (see Table 2) were used for the numerical simulations shown in Figure 4. Note that

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

3 - 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_2023). 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. All sequencing data associated with

this study were submitted to the GEO repository on 2/10/2024 (GEO: GSEXXXX—will be updated

when available). The mass spectrometry proteomics data have been deposited to the

ProteomeXchange Consortium via the PRIDE partner repository with the dataset identifier

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 FIGURE LEGENDS

 Figure 1. Growth rate and genome copy number in *E. coli.*

 (**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 growth rate 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. (**H**)

 Absolute and (**I**) relative growth rate in 1N (50352 from 973 cells, CJW7457) and WT (80269 datapoints

 from 12544 cells, CJW7339) cells in M9gly. (**J**) Absolute and (**K**) relative growth rate in 1N (71736

 datapoints from 909 cells, CJW7457) and WT (63367 datapoints from 6880 cells, CJW7339) cells in

 M9ala. Lines and shaded areas denote mean ± SD from three biological replicates.

 Figure 2. Lower ribosome activity explains the reduced growth rate of 1N cells. (**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 (red, slow-moving) active and (gray, fast-moving)

inactive 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 Fig. 2A, F and G). Lines and shaded areas denote mean and 95% CI

of the mean from bootstrapping.

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Figure 3. RNAP activity is reduced in 1N cells. (**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 3 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 (175,884 tracks from 1219 cells, CJW7520)

and multi-N cells (186,951 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 (red, slow-moving) active and (gray, fast-moving)

inactive 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 Fig. 3A, F and G). Also, shown is a linear

fit to multi-N data (f(x) = 4.16*10^4*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.

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Figure 4. Mathematical modeling and RNASelect concentration measurements in 1N and multi-N

cells. (**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**) A two-dimensional diagram showing how the fractions

of active RNAPs and ribosomes change with DNA concentration (colored from blue to yellow).

Experimental data (with 2D error bars) from multi-N and 1N cells were combined and shown in the

same plot. Simulated results (filled dots) are based on model A. (**E**) Plot showing the effect of DNA

limitation using the ODE model A, with respect to 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). (**F**) The phase contrast (top), HU-mCherry (middle) and SYTO

RNASelect fluorescence (bottom) images of two representative cells from a mixed population of 1N

(CRISPRi *oriC*, CJW7457) and multi-N (CRISPRi *ftsZ*, CJW7576) cells. The purple and orange ticks In the

SYTO RNASelect colorbar correspond to the average fluorescence (concentration proxy) of the multi-

N and the 1N cell respectively. (**G**) SYTO RNASelect concentration distributions for 1N and multi-N

cells (3077 cells for each population from five biological replicates). (**H**) The average 1N/multi-N SYTO

RNASelect concentration ratio (gray bar) calculated from five biological replicates (white circles). (**I**)

RNASelect concentration ratio as a function of cell area (Mean +/- SD from five biological replicates).

A single exponential decay function was fitted to the average ratios (R^2 = 97%). All RpoC-HaloTag-

JF549 concentration comparisons or ratio calculations were performed for equal numbers of 1N and

multi-N cells and overlapping cell area distributions (Figure 4 – supplement 4A).

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Figure 5. 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

with cell area. **(B)** Plot showing the protein scaling (average slopes from 2 reproducible biological

replicates, see also Figure 5 – supplement 1A-B) in 1N (x-axis) and multi-N (y-axis) cells across the

proteome (2360 proteins). The colormaps correspond 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)** Relationship between the absolute

distance of a gene from *oriC* and the slope of the protein it encodes. Data from 2268 proteins are

shown (grey markers), 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 cells, 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). **(E)** Relationship

between the distance of a gene from *oriC* and the ion intensity of its encoded protein. The protein ion

intensity was divided by the protein sequence length and the quotient was log-transformed. Data

from 2258 proteins are shown (grey markers) as well as binned data (open circles, average +/- SEM,

~370 proteins per bin). The spearman correlation is not significant (ρ = NS, p-value > 0.01). **(F)**

Correlation between average protein and mRNA slopes across the genome (2324 genes).

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SUPPLEMENTARY FIGURE LEGENDS

Figure 1 – figure supplement 1. Relationships between growth rate and cell volume across several

growth conditions and cell types of different ploidy. (**A**) 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 in M9GlyCAAT as a function of cell area. Lines and shaded

areas denote mean ± SD from 3 biological replicates. (**B**) Absolute and (**C**) 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 in M9glyCAAT. Lines and shaded areas denote mean ± SD from three experiments. The

growth rates are based on volume in this figure. (**D**) Absolute and (**E**) relative growth rate in

M9glyCAAT 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.

(**F**) Absolute growth rate 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. (**H**) Absolute and (**I**) relative growth rate in 1N (50352 from 973

cells, CJW7457) and WT (80269 datapoints from 12544 cells, CJW7339) cells in M9gly. (**J**) Absolute

and (**K**) relative growth rate in 1N (71736 datapoints from 909 cells, CJW7457) and WT (63367

datapoints from 6880 cells, CJW7339) cells in M9ala. Lines and shaded areas denote mean ± SD from

three biological replicates.

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1297 **Figure 1 – figure supplement 2. Relationships between growth rate and cell area in cell types of**

1298 **different ploidy.** (**A**) Absolute and (**B**) relative growth rate growth rate in M9glyCAAT in 1N (32735

1299 datapoints from 1568 cells, CJW7457), multi-N (14006 datapoints from 916 cells, CJW7576) and WT

1300 (19495 datapoints from 7440 cells, CJW7339) cells as a function of cell area. Lines and shaded areas

1301 denote mean ± SD from three biological replicates.

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Figure 1 – figure supplement 3. Characterization of ploidy in different cell types. (**A**) Representative

microscopy images of CRISPRi *oriC* cells expressing HU-CFP and ParB-mCherry with *parS* site at *ori1*

(CJW7517) in M9glyCAAT 210 min after addition of 0.2% L-arabinose. Scale bar: 1 μm. (**B**)

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 bar: 1 μm. (**C**) 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.

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1312   **Figure 1 – figure supplement 4. Determination of absolute growth rate of ppGpp^0 (CJW7518) and**

1313   **Δ*recA* (CJW7522) cells grown in M9glyCAAT as a function of cell area.** Lines and shaded areas denote

1314   mean ± SD from two biological replicates. Also shown are the data for 1N (CJW7457) and multi-N

1315   (CJW7576) cells from Figure 1C.

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Figure 1 – figure supplement 5. Validation of stable growth conditions under microscope

observation. (**A**) Plot showin the absolute growth rate of 1N (CJW7457) cells grown 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. The data for 1N (CJW7457) and multi-N (CJW7576) cells presented in Figure 1C are

also shown for comparison; these cells were grown on an agarose pad for 6 h. Lines and shaded areas

denote mean ± SD from two biological replicates. (**B**) Plot showing the relative growth rate of WT

(CJW7339) cells in M9glyCAAT grown after placing them on an agarose pad. Lines and shaded areas

denote mean ± SD from three biological replicates.

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1326 **Figure 1 – figure supplement 6. DNA-dependent growth in *Caulobacter crescentus*.** (**A**) Plot showing

1327 the absolute and (**B**) relative growth rate of 1N (DnaA depletion, strain CJW4823, 87 cells) and multi-

1328 N (FtsZ depletion, strain CJW3673, 181 cells) *C. crescentus* as a function of cell area. Lines and shaded

1329 areas denote mean ± SD from three biological replicates. (**C**) Example images of 1N and multi-N *C.*

1330 *crescentus* cells with ploidy distinguished by the number of ParB-eCFP foci. Scale bar: 2 µm.

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1332 **Figure 2 – figure supplement 1. Determination of RpsB-msfGFP concentration in 1N cells.** Plot

1333 showing the RpsB-msfGFP fluorescence concentration in 1N (CJW7478) cells grown in (**A**) M9gly (from

1334 three experiments) or (**B**) M9ala (from two experiments) as a function of cell area. Lines and shaded

1335 areas denote mean ± SD between the biological replicates.

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1337 **Figure 2 – figure supplement 2. Diffusive characteristics of labeled ribosomes in rifampicin-treated**

1338 **WT cells.** (**A**) Plot showing the probability density of apparent diffusion coefficients (D_a) of JF549-

1339 labeled RpsB-HaloTag in WT cells (CJW7528) treated with 200 µg/mL rifampicin for 30 min. Only tracks

1340 of length ≥10 are included. Also shown is D_a fitted by three-state Gaussian mixture model (GMM)

1341 (mean ± SEM). Data are from three biological replicates.

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Figure 2 – figure supplement 3. Diffusive characteristics of labeled ribosomes in 1N cells as a

function of cell area. Plots showing the probability density of apparent diffusion coefficients (D_a) of

JF549-labeled RpsB-HaloTag in 1N cells (CJW7529) in M9glyCAAT at different cell areas. Also shown is

D_a fitted by three-state Gaussian mixture model (GMM). Only tracks of length ≥10 are included. Data

are from three biological replicates.

Figure 2 – figure supplement 4. Characterization of ribosome diffusion and active fraction in poor

media conditions. (**A**) 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. (**B**) Same

as (A) for cells grown in M9ala. (**C**) Plot showing probability density of D_a of JF549-labeled RpsB-

HaloTag in WT cells (CJW7528) grown M9gly. Only tracks of length ≥10 are included. Also shown is D_a

fitted by three-state Gaussian mixture model (GMM) (mean ± SEM). (**D**) Same as (C) but for cells grown

in M9ala. (**E**) 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. (**F**) same as (E)

but for cells grown in M9ala. (**G**) Plot showing the total active ribosome amount (left y-axis) and the

absolute growth rate (right y-axis) of 1N and multi-N cells (from Figure 1C) 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. Also, shown is a linear fit to WT data (f(x) =

$2.99*10^4*x$, R^2 0.97). Lines and shaded areas denote mean and 95% CI of the mean from

bootstrapping. All data are from three biological replicates. (**H**) Same as (G) but for cells grown in

M9Ala. Here the linear fit to the WT data is f(x) = $1.90*10^4*x$, R^2 0.99.

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Figure 3 – figure supplement 1. Determination of RpoC-YFP concentration in 1N cells. (**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).

Figure 3 – figure supplement 2. Diffusive characteristics of labeled RNAPs in rifampicin-treated WT

cells. Plot showing the probability density of apparent diffusion coefficients (D_a) of JF549-labeled

RpoC-HaloTag in WT cells (CJW7519) treated with 200 µg/mL rifampicin for 30 min. Also shown is D_a

fitted by three-state Gaussian mixture model (GMM) (mean ± SEM). Only tracks of length ≥10 are

included. Data are from three biological replicates.

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1376   **Figure 3 – figure supplement 3. Diffusive characteristics of labeled RNAPs in 1N cells of different cell**

1377   **areas.** Plots showing the apparent diffusion coefficients (D_a) of JF549-labeled RpoC-HaloTag in 1N cells

1378   (CJW7520) of different cell areas. Cells were grown in M9glyCAAT. Also shown is D_a fitted by three-

1379   state Gaussian mixture model (GMM). Only tracks of length ≥10 are included. Data is from three

1380   biological replicates.

1381

Figure 3 – figure supplement 4. Characterization of RNAP diffusion and active fraction in poor media

conditions. (**A**) 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. (**B**) Same as (A) but for cells grown in

M9ala. (**C**) 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). (D) Same as (C) but for cells grown in M9ala. (E) Plots showing the fraction of active

RNAPs in individual WT (CJW7519) and 1N (CJW7520) cells (dots) grown in M9gly as a function of cell

area. Only cells with ≥50 tracks are included. (**F**) Same as (E) but for cells grown in M9ala. (**G**) Plot

showing the total amount of active RNAPs was calculated by multiplying the total amount of RNAPs

by the fraction of active RNAPs in WT and 1N cells grown in M9gly as a function of cell area. Also,

shown is a linear fit to WT data (f(x) = 3.99*10^4*x, R^2 0.90). Shaded areas denote 95% confidence

interval (CI) of the mean from bootstrapping. All data are from three biological replicates. (**H**) Same

as (G) but for cells grown in M9ala. Here, the linear fit for WT data is f(x) = 3.21*10^4*x, R^2 0.95.

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Figure 3 – figure supplement 5. 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 0, 60, and

120 min after 0.2% L-arabinose induction of CRISPRi. Different shades of gray represent two

independent experiments.

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Figure 4 – figure supplement 1. Comparison between experimental results from the M9glyCAAT

condition and simulation results using model B. (**A-C**) Plots comparing simulation results of model B

(solid lines) with experimental data (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**) A two-dimensional

diagram showing how the fractions of active RNAPs and ribosomes change with DNA concentration

(colored from blue to yellow). Experimental data (with 2D error bars) from multi-N and 1N cells were

combined and shown in the same plot.

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Figure 4 – figure supplement 2. Comparison between experimental results from the M9gly and

M9ala conditions and simulation results using model A. (**A-C**) Plots comparing simulation results of

model A (solid lines) with experimental data (dots) and averages (open squares) in the M9gly

condition. The wild-type and 1N cells are indicated as black and yellow, respectively. (**D-F**) Plots

comparing simulation results of model A (solid lines) with experimental data (dots) and averages

(open squares) in the M9ala condition. The wild-type and 1N cells are indicated as black and yellow,

respectively. (**A,D**) The relation between the absolute growth rate ($\frac{dA}{dt}$) and cell area (A). (**B,E**) The

relation between the active RNAP fraction and cell area. (**C,F**) The relation between the active

ribosome fraction and cell area.

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Figure 4 – figure supplement 3. 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 rate r_1 increase 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.

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Figure 4 – figure supplement 4. Cell sampling to match cell size distribution in mixed populations of

1N and multi-N cells. Comparison of the cell area distributions of 1N and multi-N cells before and

after random sampling. Single cells were sampled for each biological replicate and cell area bin such

that the area distributions and numbers of 1N and multi-N cells overlapped. Bins with less than 50

cells from either population were removed from the analysis. Cell area distributions from mixed

CJW7457 (CRISPRi *oriC*) and CJW7576 (CRISPRi *ftsZ*) populations stained with SYTO RNASelect

(aggregated data from five biological replicates)

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Figure 4 – figure supplement 5. 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. The blue and orange ticks In the RpoC-HaloTag-JF549 color bar correspond to the

average fluorescence (concentration proxy) of the multi-N and the 1N cell, respectively. (**B**) Same as

Figure 4– figure supplement 4, except for CJW7520 (CRISPRi *oriC*) and CJW7527 (CRISPRi *ftsZ*) cells in

which RpoC-HaloTag was stained with the JF549 dye (aggregated data from two biological replicates).

(**C**) Distributions of RpoC-HaloTag-JF549 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 (see Materials

and Methods). (**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.

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Figure 5 – figure supplement 1. Comparison of protein and mRNA scaling between biological

replicates. (**A**) Correlation of protein slopes across the proteome (2360 proteins) between two

biological replicates for 1N cells. The indicated Spearman correlation (ρ) is significant (p-value < 10⁻¹⁰.

(**B**) Same as (A) but for multi-N cells. (**C**) Correlation of RNA slopes across the genome (3446 mRNAs)

between two biological replicates for 1N cells. The indicated Spearman correlation shown (ρ) is

significant (p-value < 10⁻¹⁰).

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1464 **Figure 5 – figure supplement 2. Protein slopes relative to protein ion intensity for 1N-rich cells.** The

1465 summed ion intensity of each protein was divided by the protein sequence length and the quotient

1466 was log-transformed. The locations of selected proteins are annotated.

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1468 **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	cell volume / protein number	$10^{-6}\mu m^3$	Cell volumes of different culture conditions were measured in this work.
c'	cell area / protein number	$10^{-6}\mu m^2$	Cell area of different culture conditions were 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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1473 **Table 2: Initial and optimized model parameters**
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Para-meter	Unit	Initial estimation			Optimized parameters			
		M9gly CAA	M9gly	M9ala	M9glyCAA (model A)	M9glyCAA (model B)	M9gly (model A)	M9ala (model A)
r_1	10^{-3}/min	1.99	0.89	0.60	1.22	1.76	0.64	0.46
r_2	10^{-3}/min	20.0	8.21	3.70	22.4	22.5	15.3	13.6
K_1	$1/\mu m^3$	1.40	2.99	3.03	1.17	1.55	3.02	2.78
K_2	$1/\mu m^3$	622	1807	1467	797	532	1836	1513
δ	1/min	0.96	0.96	0.96	1.27	1.31	1.02	0.79
c	$10^{-6}\mu m^3$	0.28	0.39	0.53	0.28	0.18	0.15	0.30
c'	$10^{-6}\mu m^2$	0.47	0.62	1.06	-	-	-	-
X_{ini}	10^2/cell	20.2	7.21	3.17	-	-	-	-
Y_{ini}	10^6/cell	3.82	1.77	0.95	-	-	-	-
$[Z]_{avg}$	genome /cell	1.40	1.99	2.02	-	-	-	-

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1476 **Table 3. Strains used in this study**. The abbreviations *kan*, *cat*, and *spec* refer to gene cassette

1477 insertions conferring resistance to kanamycin, chloramphenicol, and spectinomycin, respectively.

1478 These insertions are flanked by Flp site-specific recombination sites (*frt*) that allow the removal of the

1479 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 ɸCr30 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*	The kanamycin resistance cassette was excised from CJW7457 by

	araBAD::*dCas9 galM<PBBa-J23119-sgRNA(oriC)-(S. pyogenes terminator)-(rrnB terminator)>gmpA hupA*::*hupA-mCherry rpoC*::*rpoC-ygfp-kan*	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 terminator)-(rrnB terminator)>gmpA gtrA*::*P58-mCherry-parB(pMT1) parS(pMT1) at ori1 hupB*::*hupB-cfp-kan*	The strain was generated by first moving *gtrA*::*P58-mCherry-parB(pMT1)-cat* (Wiktor et al., 2021) into SJ_XTL676 by P1 transduction. 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 terminator)>gmpA hupA*::*hupA-mCherry ΔrecA*::*kan*	*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 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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1483   **Table 4. Oligonucleotides used in this study.**

Name	Sequence
AP0039	ACCCAACTTAATCGCTGTAGGCTGGAGCTGCTTCG
AP0040	ATTAATTGCGTTGCGCAGTTCCCTACTCTCGCATGGG
AP0041	GAGAGTAGGGAACTGCGCAACGCAATTAATGTGAGTTAGC
AP0042	CAGCTCCAGCCTACAGCGATTAAGTTGGGTAACGCCA
AP0078	ATCAAACATCCTGCCAACTCCATGTGACAAACCGTCATCTTCGGCTACTTGCAACGCAA TTAATGTGAGTTAGC
AP0079	ACAAACATTAATAACGAAGAGATGACAGAAAAATTTTCATTCTGTGACAGCCCTGATTC CGTGAGGATGC
JSG_018	GCCCGAGGGCACGTGACGCGTCTCCGGATG
JSG_019	ACCTCGGCGATCGCGAACGCCGAAGCTAGCGAATTCGTGGATC
JSG_020	GAATTCGCTAGCTTCGGCGTTCGCGATCGCCGAGGTG
JSG_021	GGCATGGACGAGCTGTACAAGTAAGCCACCCAAGTTTTAGTAAGCG
JSG_022	CGCTTTACTGGGTACGCTTACTAAAACTTGGGTGGCTTACTTGTACAGCTCGTCCATGC C
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	GCCTGGCAGAACTGCTGAACGCAGGTCTGGGCGGTTCTGATAACGAGTAATCGGCTG GCTCCGCTGCT
JSG_149	CATAAAAAAACCCGCCGAAGCGGGTTTTTACGTTATTTGCGGATTAACGAGGATCCCA TATGAATATCCTCCTT

JSG_157	GTTCTCAGGATCTGGCTTCCCAGGCGGAAGAAAGCTTCGTAGAAGCTGAGTCGGCTGG CTCCGCTGCT
JSG_158	TTGCCGCCTTTCTGCAACTCGAACTATTTTGGGGGAGTTATCAAGCCTTAGGATCCCAT ATGAATATCCTCCTT
JSG_173	AAAAAAGCAAAAGGGCCGCAGATGCGACCCTTGTGTATCAAACAAGACGAGTGTAGG CTGGAGCTGCTTC
JSG_174	CAACAGAACATATTGACTATCCGGTATTACCCGGCATGACAGGAGTAAAATGTACAAG AAAGCTGGGTACG
NT157	TATGGATCCTGTTTTTCACCACGCCAATTTCATGG
NT158	TATGGTACCGAGGTTGAAAAGCGTGGTG

1484

Figure 1

Figure 2

Figure 3

Figure 4

Figure 5

Fig 1 Fig supplement 1

Fig 1 Fig supplement 2

Fig 1 Fig supplement 3

Fig 1 Fig supplement 4

Fig 1 Fig supplement 5

Fig 1 Fig supplement 6

Fig 2 Fig supplement 1

Fig 2 Fig supplement 2

Fig 2 Fig supplement 3

Fig 2 Fig supplement 4

Fig 3 Fig supplement 1

Fig 3 Fig supplement 2

RNAP CRISPRi *oriC* M9glyCAAT

Fig 3 Fig supplement 3

Fig 3 Fig supplement 4

Fig 3 Fig supplement 5

Fig 4 Fig supplement 1

Fig 4 Fig supplement 2

Fig 4 Fig supplement 3

Fig 4 Fig supplement 4

Fig 4 Fig supplement 5

Fig 5 Fig supplement 1

Fig 5 Fig supplement 2