

# Fundamental limits on the rate of bacterial cell division

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<sup>15</sup> **Abstract** Recent years have seen an experimental deluge interrogating the relationship between bacterial  
<sup>16</sup> growth rate, cell size, and protein content, quantifying the abundance of proteins across growth conditions with  
<sup>17</sup> unprecedented resolution. However, we still lack a rigorous understanding of what sets the scale of these  
<sup>18</sup> quantities and when protein abundances should (or should not) depend on growth rate. Here, we seek to  
<sup>19</sup> quantitatively understand this relationship across a collection of *Escherichia coli* proteomic data covering  $\approx 4000$   
<sup>20</sup> proteins and 36 growth rates. We estimate the basic requirements for steady-state growth by considering key  
<sup>21</sup> processes in nutrient transport, energy generation, cell envelope biogenesis, and the central dogma. From these  
<sup>22</sup> estimates, ribosome biogenesis emerges as a primary determinant of growth rate. We expand on this  
<sup>23</sup> assessment by exploring a model of proteomic regulation as a function of the nutrient supply, revealing a  
<sup>24</sup> mechanism that ties cell size and growth rate to ribosomal content.

<sup>25</sup>

## <sup>26</sup> Introduction

<sup>27</sup> The observed range of bacterial growth rates is enormously diverse. In natural environments, some microbial  
<sup>28</sup> organisms may double only once per year (*Mikucki et al., 2009*) while in comfortable laboratory conditions, growth  
<sup>29</sup> can be rapid with several divisions per hour (*Schaechter et al., 1958*). This six order-of-magnitude difference in  
<sup>30</sup> time scales encompasses different microbial species and lifestyles, yet even for a single species such as *Escherichia*  
<sup>31</sup> *coli*, the growth rate can be modulated over a comparably large scale by tuning the type and amount of nutrients  
<sup>32</sup> in the growth medium. This remarkable flexibility in growth rate illustrates the intimate relationship between  
<sup>33</sup> environmental conditions and the rates at which cells convert nutrients into new cellular material – a relationship  
<sup>34</sup> that has remained a major topic of inquiry in bacterial physiology for over a century (*Jun et al., 2018*).

<sup>35</sup> Jacques Monod once remarked that “the study of the growth of bacterial cultures does not constitute a spe-  
<sup>36</sup> cialized subject or branch of research, it is the basic method of Microbiology.” Those words ring as true today as  
<sup>37</sup> they did when they were written 70 years ago (*Monod, 1949*) with the quantitative power of this “method” recently  
<sup>38</sup> undergoing renaissance. Many of the key questions addressed by the pioneering efforts in the middle of the last  
<sup>39</sup> century can be revisited by examining them through the lens of the increasingly refined molecular census that is  
<sup>40</sup> available for bacteria such as the microbial workhorse *E. coli*.

<sup>41</sup> Several of the evergreen questions about bacterial growth and physiology that were originally raised by micro-

42 biologists in the middle of the 20th century can now be reframed in light of this newly available data. For example,  
43 what biological processes are the primary determinants for how quickly bacterial cells can grow and reproduce?  
44 How do cells modulate the absolute numbers and relative ratios of their molecular constituents as a function of  
45 changes in growth rate or nutrient availability? In this paper, we begin by considering these two questions from  
46 two distinct angles. First, as a result of an array of high-quality proteome-wide measurements of *E. coli* under  
47 diverse growth conditions, we have a census that allows us to explore how the number of key molecular players  
48 change as a function of growth rate. Here, we have assembled a singular data set using measurements collected  
49 over the past decade via mass spectrometry (*Schmidt et al., 2016; Peebo et al., 2015; Valgepea et al., 2013*) or  
50 ribosomal profiling (*Li et al., 2014*) of the composition of the *E. coli* proteome across 36 unique growth rates (see  
51 the Appendix Section "Experimental Details Behind Proteomic Data" for a further discussion of the data). Second,  
52 by compiling molecular turnover rate measurements for many of the fundamental processes associated with bac-  
53 terial growth, we make quantitative estimates of key cellular processes (schematized in *Figure 1*) to determine  
54 whether our current understanding of the dynamics of these processes are sufficient to explain the magnitude of  
55 the observed protein copy numbers across conditions (see *Box 1* describing the philosophy behind this approach).  
56 The census, combined with these estimates, provide a window into the question of whether the rates of central  
57 processes such as energy generation or DNA synthesis are regulated systematically as a function of cell growth  
58 rate by altering protein copy number.

59 Throughout our estimates, we consider an archetypal growth rate of  $\approx 0.5 \text{ hr}^{-1}$  corresponding to a doubling  
60 time of  $\approx 5000$  seconds, as the data sets examined here heavily sample this growth regime. While we formulate  
61 point estimates for the protein abundances at this division time, we also consider how these values will vary  
62 at other growth rates due to changes in cell size, surface area, and chromosome copy number (*Taheri-Araghi*  
63 *et al., 2015; Harris and Theriot, 2018*). For the majority of the processes considered, we find that the protein copy  
64 numbers appear tuned for the task of cell doubling across a continuum of growth rates. Thus, our understanding  
65 of the kinetics of myriad biological processes is sufficient to quantitatively explain the observed abundances of  
66 these proteins.

67 From these estimates, it emerges that translation, particularly the synthesis of ribosomal proteins, is a plausi-  
68 ble candidate that limits the rate of cell division in *E. coli*. We reach this conclusion by considering that ribosome  
69 synthesis is 1) a rate limiting step for the *fastest* bacterial division, and 2) a major determinant of bacterial growth  
70 across the nutrient conditions we have considered under steady state, exponential growth. This enables us to  
71 suggest that the long-observed correlation between growth rate and cell size (*Schaechter et al., 1958; Si et al.,*  
72 *2017*) can be simply attributed to the increased absolute number of ribosomes per cell under conditions support-  
73 ing extremely rapid growth. To better understand how the observed alterations in absolute protein abundances,  
74 and in particular, changes in ribosome copy number, influence growth rate across different nutrient conditions  
75 we consider a minimal model of cellular growth. Our conclusions from these analyses provide important insight  
76 into how *E. coli* regulates growth across conditions of differing nutrient availability and identifies fundamental  
77 constraints in bacterial growth more broadly.

## 118 Nutrient Transport

119 We begin by considering the critical transport processes diagrammed in *Figure 1(A)*. In order to build new cel-  
120 lular mass, the molecular and elemental building blocks must be scavenged from the environment in different  
121 forms. Carbon, for example, is acquired via the transport of carbohydrates and sugar alcohols with some carbon  
122 sources receiving preferential treatment in their consumption (*Monod, 1947*). Phosphorus, sulfur, and nitrogen,  
123 on the other hand, are harvested primarily in the forms of inorganic salts, namely phosphate, sulfate, and ammo-  
124 nium/ammonia (*Jun et al., 2018; Assentoft et al., 2016; Stasi et al., 2019; Antonenko et al., 1997; Rosenberg et al.,*  
125 *1977; Willsky et al., 1973*). All of these compounds have different membrane permeabilities (*Phillips, 2018*) and  
126 most require some energetic investment either via ATP hydrolysis or through the proton electrochemical gradient  
127 to bring the material across the hydrophobic cell membrane.

128 The elemental composition of *E. coli* has received much quantitative attention over the past half century (*Neid-*  
129 *hardt et al., 1991; Taymaz-Nikerel et al., 2010; Heldal et al., 1985; Bauer and Ziv, 1976*), providing us with a starting  
130 point for estimating how many atoms of each element must be scavenged from the environment. A synthesis of

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## Box 1. The Rules of Engagement for Order-Of-Magnitude Estimates

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This work relies heavily on "back-of-the-envelope" estimates to understand the growth-rate dependent abundances of molecular complexes. This moniker arises from the limitation that any estimate should be able to fit on the back of a postage envelope. As such, we must draw a set of rules governing our precision and sources of key values.

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**The rule of "one, few, and ten".** The philosophy behind order-of-magnitude estimates is to provide an estimate of the appropriate scale, not a prediction with many significant digits. We therefore define three different scales of precision in making estimates. The scale of "one" is reserved for values that range between 1 and 2. For example, If a particular process has been experimentally measured to transport 1.87 protons for a process to occur, we approximate this process to require 2 protons per event. The scale of "few" is reserved for values ranging between 3 and 7. For example, we will often use Avogadro's number to compute the number of molecules in a cell given a concentration and a volume. Rather than using Avogadro's number as  $6.02214 \times 10^{23}$ , we will approximate it as  $5 \times 10^{23}$ . Finally, the scale of "ten" is reserved for values which we know within an order of magnitude. If a particular protein complex is present at 883 copies per cell, we say that it is present in approximately  $10^3$  copies per cell. These different scales will be used to arrive at simple estimates that report the expected scale of the observed data. Therefore, the estimates presented here should not be viewed as hard-and-fast predictions of precise copy numbers, but as approximate lower (or upper) bounds for the number of complexes that may be needed to satisfy some cellular requirement.

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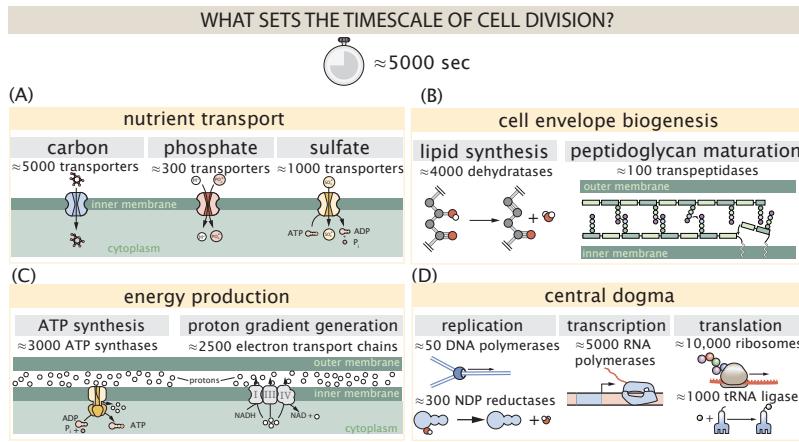
Furthermore, we use equality symbols (=) sparingly and frequently defer to approximation ( $\approx$ ) or scaling ( $\sim$ ) symbols when reporting an estimate. When  $\approx$  is used, we are implicitly stating that we are confident in this estimate within a factor of a few. When a scaling symbol  $\sim$  is used, we are stating that we are confident in our estimate to within an order of magnitude.

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**The BioNumbers Database as a source for values.** In making our estimates, we often require approximate values for key cellular properties, such as the elemental composition of the cell, the average dry mass, or approximate rates of synthesis. We rely heavily on the BioNumbers Database ([bionumbers.hms.harvard.edu](http://bionumbers.hms.harvard.edu), *Milo et al. (2010)*) as a repository for such information. Every value we draw from this database has an associated BioNumbers ID number, abbreviated as BNID, and we provide this reference in grey-boxes in each figure.

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**Uncertainty in the data sets and the accuracy of an estimate.** The data sets presented in this work are the products of careful experimentation with the aim to report, to the best of their ability, the absolute copy numbers of proteins in the cell. These data, collected over the span of a few years, come from different labs and use different internal standards, controls, and even techniques (discussed further in Appendix Experimental Details Behind Proteomic Data). As a result, there is notable disagreement in the measured copy numbers for some complexes across data sets. In assessing whether our estimates could explain the observed scales and growth-rate dependencies, we also considered the degree of variation between the different data sets. For example, say a particular estimate undercuts the observed data by an order of magnitude. If all data sets agree within a factor of a few of each other, we revisit our estimate and consider what we may have missed. However, if the data sets themselves disagree by an order of magnitude, we determine that our estimate is appropriate given the variation in the data.



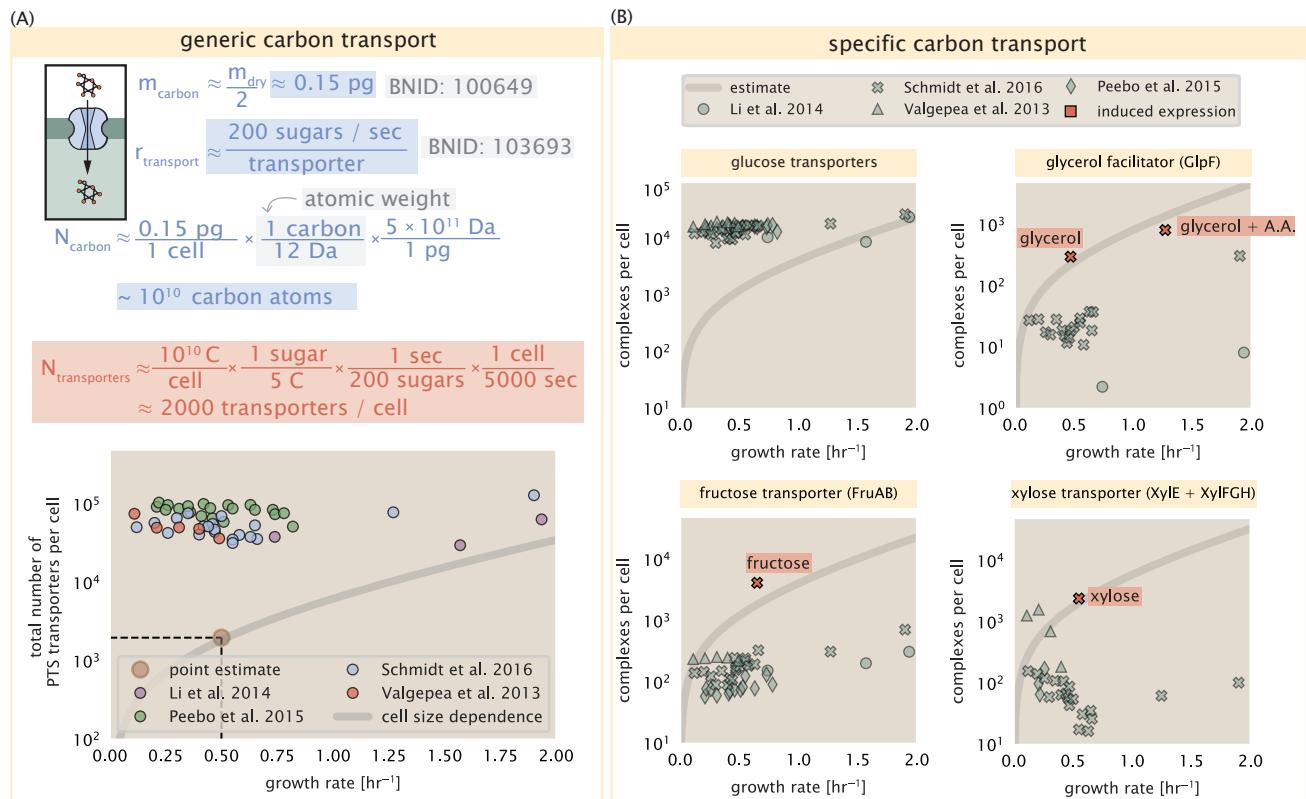
**Figure 1. Transport and synthesis processes necessary for cell division.** We consider an array of processes necessary for a cell to double its molecular components, broadly grouped into four classes. These categories are (A) nutrient transport across the cell membrane, (B) cell envelope biogenesis, (C) energy production (namely, ATP synthesis), and (D) processes associated with the central dogma. Numbers shown are the approximate number of complexes of each type observed at a growth rate of  $0.5 \text{ hr}^{-1}$ , or a cell doubling time of  $\approx 5000 \text{ s}$ .

these studies presents an approximate dry mass composition of  $\approx 50\%$  carbon (BNID: 100649; see **Box 1** for explanation of BNID references),  $\approx 15\%$  nitrogen (BNID: 106666),  $\approx 3\%$  phosphorus (BNID: 100653), and  $1\%$  sulfur (BNID: 100655) with remainder being attributable to oxygen, hydrogen, and various transition metals. We use this stoichiometric breakdown to estimate the abundance and growth rate dependence of a variety of transporters responsible for carbon uptake, and provide more extensive investigation of the other critical elements – phosphorus, sulfur, and nitrogen – in the Appendix Section "Additional Estimates of Fundamental Biological Processes".

Using  $\approx 0.3 \text{ pg}$  as the typical *E. coli* dry mass at a growth rate of  $\approx 0.5 \text{ hr}^{-1}$  (BNID: 103904), coupled with an approximation that  $\approx 50\%$  of this mass is carbon, we estimate that  $\sim 10^{10}$  carbon atoms must be brought into the cell in order to double all of the carbon-containing molecules (**Figure 2(A)**, top). Typical laboratory growth conditions provide carbon as a single class of sugar (such as glucose, galactose, or xylose) often transported cross the cell membrane by a transporter complex specific to that particular sugar. One such mechanism of transport is via the PTS system, which is a highly modular system capable of transporting a diverse range of sugars with high specificity (*Escalante et al., 2012*). The glucose-specific component of this system transports  $\approx 200$  glucose molecules ( $\approx 1200$  carbon atoms) per second per transporter (BNID: 114686). Making the assumption that this is a typical sugar transport rate for the PTS system, coupled with the need to transport  $\sim 10^{10}$  carbon atoms, we then expect on the order of  $\approx 2000$  transporters must be expressed per cell in order to bring in enough carbon atoms (**Figure 2(A)**, top).

We find, however, that this estimate is exceeded by several fold by experimental measurements (**Figure 2(A)**, bottom), implying that the cell is capable of transporting more carbon atoms than strictly needed for biosynthesis. We can also abstract this calculation to consider any particular growth rate given knowledge of the cell density and volume as a function of growth rate and direct the reader to the Appendix Section "Extending Estimates to a Continuum of Growth Rates" for more information. This abstraction, shown as a grey line in **Figure 2(A)**, reveals an excess of transporters even at faster growth rates. This contrasts with our observations for uptake of phosphorus and sulfur, which turn out to align well with our expectations across different growth conditions (**Figure 2**–**Figure Supplement 1** and discussed further in the Appendix Section "Additional Estimates of Fundamental Biological Processes").

It is important to note that so far we have neglected any specifics of the regulation of the carbon transport system. Using the diverse array of growth conditions available in the data, we can explore how individual carbon transport systems depend on specific carbon availability. In **Figure 2(B)**, we show the total number of carbohydrate transporters specific to different carbon sources. A striking observation, shown in the top-left plot of **Figure 2(B)**, is the constancy in the expression of the glucose-specific transport systems, an observation that stands in contrast with other species of transporters. Additionally, we note that the total number of glucose-specific transporters is



**Figure 2. The abundance of carbon transport systems across growth rates.** (A) A simple estimate for the minimum number of generic carbohydrate transport systems (top) assumes  $\sim 10^{10}$  C are needed to complete division, each transported sugar contains  $\approx 5$  C, and each transporter conducts sugar molecules at a rate of  $\approx 200$  per second. Bottom plot shows the estimated number of transporters needed at a growth rate of  $\approx 0.5$  per hr (light-brown point and dashed lines). Colored points correspond to the mean number of complexes involved in carbohydrate import (complexes annotated with the Gene Ontology terms GO:0009401 and GO:0098704) for different growth conditions across different published datasets. (B) The abundance of various specific carbon transport systems plotted as a function of the population growth rate. The rates of substrate transport differ between these transporter species. To compute the continuum growth rate estimate (grey line), we used the following transport rates for each transporter species: 200 glucose- $s^{-1}$  (BNID: 103693), 2000 glycerol- $s^{-1}$  (**Lu et al., 2003**), 200 fructose- $s^{-1}$  (assumed to be similar to PtsI, BNID: 103693), and 50 xylose- $s^{-1}$  (assumed to be comparable to LacY, BNID: 103159). Red points and highlighted text indicate conditions in which the only source of carbon in the growth medium induces expression of the transport system. Grey lines in (A) and (B) represent the estimated number of transporters per cell at a continuum of growth rates.

**Figure 2-Figure supplement 1.** Estimates and observed abundances of phosphate and sulfate transporters.

<sup>163</sup> tightly distributed at  $\approx 10^4$  per cell, the approximate number of transporters needed to sustain rapid growth of  
<sup>164</sup> several divisions per hour. This illustrates that *E. coli* maintains a substantial number of complexes present for  
<sup>165</sup> transporting glucose regardless of growth condition, which is known to be the preferential carbon source (*Monod*,  
<sup>166</sup> 1947; *Liu et al.*, 2005; *Aidelberg et al.*, 2014).

<sup>167</sup> Many metabolic operons are regulated with dual-input logic gates that are only expressed when glucose con-  
<sup>168</sup> centrations are low and the concentration of other carbon sources are elevated (*Gama-Castro et al.*, 2016; *Zhang*  
<sup>169</sup> *et al.*, 2014b; *Gama-Castro et al.*, 2016; *Belliveau et al.*, 2018; *Ireland et al.*, 2020). Points colored in red in *Fig-*  
<sup>170</sup> *ure 2(B)* (labeled by red text-boxes) correspond to growth conditions in which the specific carbon source (glycerol,  
<sup>171</sup> xylose, or fructose) is present as the sole source of carbon. The grey lines in *Figure 2(B)* show the estimated  
<sup>172</sup> number of transporters needed at each growth rate to satisfy the cellular carbon requirement, adjusted for the  
<sup>173</sup> specific carbon source in terms of number of carbon atoms per molecule and the rate of transport for the partic-  
<sup>174</sup> ular transporter species. These plots show that, even in the absence of the particular carbon source, expression  
<sup>175</sup> of the transporters is maintained on the order of  $\sim 10^2$  per cell. The low but non-zero abundances may reflect the  
<sup>176</sup> specific regulatory logic involved, requiring that cells are able to transport some minimal amount of an alternative  
<sup>177</sup> carbon source in order to induce expression of these alternative carbon-source systems.

### <sup>178</sup> **Limits on Transporter Expression**

<sup>179</sup> If acquisition of nutrients was a limiting process in cell division under the typical growth conditions explored here,  
<sup>180</sup> the growth rate could be theoretically increased simply by expressing more transporters, but is this feasible at a  
<sup>181</sup> physiological level? A sway to approach this question is to compute the amount of space in the bacterial membrane  
<sup>182</sup> that could be occupied by nutrient transporters. Considering a rule-of-thumb for the surface area of *E. coli* of  
<sup>183</sup> about  $5 \mu\text{m}^2$  (BNID: 101792), we expect an areal density for 2000 transporters to be approximately a few hundred  
<sup>184</sup> transporters/  $\mu\text{m}^2$ . For a typical transporter occupying about  $50 \text{ nm}^2$ , this amounts to about only  $\approx 1\%$  of the  
<sup>185</sup> total inner membrane surface area (*Szenk et al.*, 2017). Bacterial cell membranes typically have densities of  $10^5$   
<sup>186</sup> proteins/ $\mu\text{m}^2$  (*Phillips*, 2018), with roughly 60 % of the surface area occupied by protein (BNID: 100078), implying  
<sup>187</sup> that the cell could easily accommodate more transporters. There are, however, additional constraints on the  
<sup>188</sup> space that can be devoted to nutrient uptake due to occupancy by proteins involved in processes like cell wall  
<sup>189</sup> synthesis and energy production, and we will consider this further in the coming sections.

### <sup>190</sup> **Cell Envelope Biogenesis**

<sup>191</sup> In contrast to nutrient transporters, which support the synthesis of biomolecules throughout the cell and therefore  
<sup>192</sup> need to scale with the cell size, here we must consider the synthesis of components that will need to scale with  
<sup>193</sup> the surface area of the cell. *E. coli* is a rod-shaped bacterium with a remarkably robust length-to-width aspect  
<sup>194</sup> ratio of  $\approx 4:1$  (*Harris and Theriot*, 2018; *Ojkic et al.*, 2019). Assuming this surface area is approximately the same  
<sup>195</sup> between the inner and outer membranes of *E. coli*, and the fact that each membrane is itself a lipid bilayer, our  
<sup>196</sup> rule-of-thumb of  $5 \mu\text{m}^2$  per surface suggests a total membrane surface area of  $\approx 20 \mu\text{m}^2$  (see the Appendix Section  
<sup>197</sup> "Estimation of Cell Size and Surface Area" for a description of the calculation of cell surface area as a function of  
<sup>198</sup> cell size). In this section, we will estimate the number of key protein complexes needed to synthesize the lipids as  
<sup>199</sup> well as the complexes involved in assembling the peptidoglycan scaffold that make up the cell envelope.

### <sup>200</sup> **Lipid Synthesis**

<sup>201</sup> The dense packing of the membrane with proteins means that the cell membranes are not composed entirely  
<sup>202</sup> of lipid molecules, with only  $\approx 40\%$  of the membrane area is occupied by lipids (BNID: 100078). Using a rule-of-  
<sup>203</sup> thumb of  $0.5 \text{ nm}^2$  as the surface area of the typical lipid (BNID: 106993), we can estimate  $\sim 2 \times 10^7$  lipids per cell,  
<sup>204</sup> which is in close agreement with experimental measurements (BNID: 100071, 102996).

<sup>205</sup> The membranes of *E. coli* are composed of a variety of different lipids, each of which are unique in their struc-  
<sup>206</sup> tures and biosynthetic pathways (*Sohlenkamp and Geiger*, 2016). Recently, a combination of stochastic kinetic  
<sup>207</sup> modeling (*Ruppe and Fox*, 2018) and *in vitro* kinetic measurements (*Ranganathan et al.*, 2012; *Yu et al.*, 2011)  
<sup>208</sup> have revealed remarkably slow steps in the fatty acid synthesis pathways which may serve as the rate limiting  
<sup>209</sup> reactions for making new membrane phospholipids in *E. coli*. One such step is the removal of hydroxyl groups  
<sup>210</sup> from the fatty-acid chain by ACP dehydratase that leads to the formation of carbon-carbon double bonds. This

reaction, catalyzed by proteins FabZ and FabA (*Yu et al., 2011*), have been estimated to have kinetic turnover rates of  $\approx 1$  dehydration per second per enzyme (*Ruppe and Fox, 2018*). Thus, given this rate and the need to synthesize  $\approx 2 \times 10^7$  lipids over 5000 seconds, one can estimate that a typical cell requires  $\approx 4000$  ACP dehydratases. This is in reasonable agreement with the experimentally observed copy numbers of FabZ and FabA (*Figure 3(A)*). Furthermore, we can extend this estimate to account for the change in membrane surface area as a function of the growth rate (grey line in *Figure 3(A)*), which captures the observed growth rate dependent expression of these two enzymes.

## Peptidoglycan Synthesis

The exquisite control of bacteria over their cell shape is due primarily to a stiff, several nanometer thick mesh-work of polymerized disaccharides that makes up the cell wall termed the peptidoglycan. The formation of the peptidoglycan is an intricate process involving many macromolecular players (*Shi et al., 2018; Morgenstein et al., 2015*), whose coordinated action maintains cell shape and integrity even in the face of large-scale perturbations (*Harris and Theriot, 2018; Shi et al., 2018*). The peptidoglycan alone comprises  $\approx 3\%$  of the cellular dry mass (BNID: 1019360), making it the most massive molecule in *E. coli*. The polymerized unit of the peptidoglycan is a N-acetylglucosamine and N-acetylmuramic acid disaccharide, of which the former is functionalized with a short pentapeptide. With a mass of  $\approx 1000$  Da, this unit, which we refer to as a murein monomer, is polymerized to form long strands in the periplasm which are then attached to each other via their peptide linkers. Together, these quantities provide an estimate of  $\approx 5 \times 10^6$  murein monomers per cell.

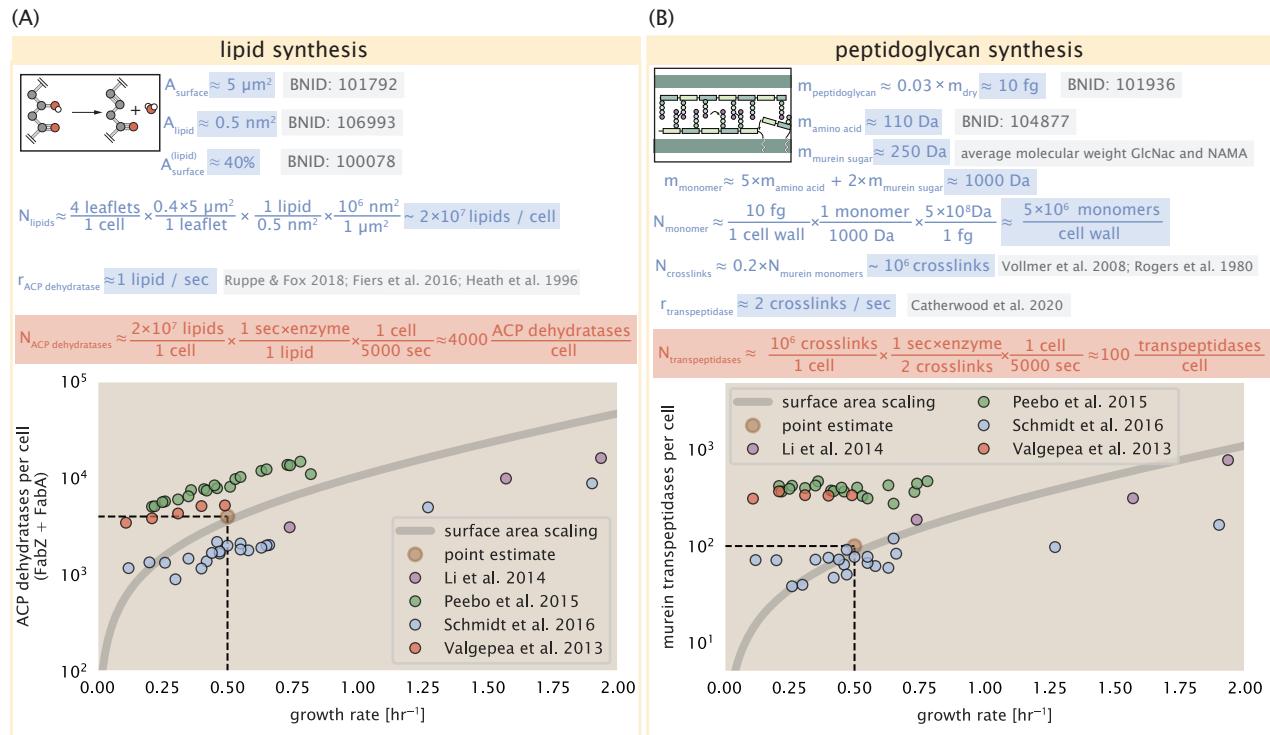
The crosslinking of the pentapeptides between adjacent glycan strands is responsible for maintaining the structural integrity of the cell wall and, in principle, each murein monomer can be involved in such a crosslink. In some microbes, such as in gram-positive bacterium *Staphylococcus aureus*, the extent of crosslinking can be large with  $> 90\%$  of pentapeptides forming a connection between glycan strands. In *E. coli*, however, a much smaller proportion ( $\approx 20\%$ ) of the peptides are crosslinked, resulting in a weaker and more porous cell wall (*Vollmer et al., 2008; Rogers et al., 1980*). The formation of these crosslinks occurs primarily during the polymerization of the murein monomers and is facilitated by a family of enzymes called transpeptidases. The four primary transpeptidases of *E. coli* have only recently been quantitatively characterized *in vivo*, via liquid chromatography mass spectrometry, which revealed a notably slow kinetic turnover rate of  $\approx 2$  crosslinking reactions formed per second per enzyme (*Catherwood et al., 2020*).

Assembling these quantities permits us to make an estimate that on the order of  $\approx 100$  transpeptidases per cell are needed for complete maturation of the peptidoglycan, given a division time of  $\approx 5000$  seconds; a value that is comparable to experimental observations [*Figure 3(B)*]. Expanding this estimate to account for the changing mass of the peptidoglycan as a function of growth rate [grey line in *Figure 3(B)*] also qualitatively captures the observed dependence in the data, though systematic disagreements between the different data sets makes the comparison more difficult.

## Limits on Cell Wall Biogenesis

While the processes we have considered represent only a small portion of proteins devoted to cell envelope biogenesis, we find it unlikely that they limit cellular growth in general. The relative amount of mass required for lipid and peptidoglycan components decrease at faster growth rates due to a decrease in their surface area to volume (S/V) ratio (*Ojkic et al., 2019*). Furthermore, despite the slow catalytic rate of FabZ and FabA in lipid synthesis, experimental data and recent computational modeling has shown that the rate of fatty-acid synthesis can be drastically increased by increasing the concentration of FabZ (*Yu et al., 2011; Ruppe and Fox, 2018*). With a proteome size of  $\approx 3 \times 10^6$  proteins, a hypothetical 10-fold increase in expression from 4000 to 40,000 ACP dehydratases would result in a paltry  $\approx 1\%$  increase in the size of the proteome. In the context of peptidoglycan synthesis, we note that our estimate considers only the transpeptidase enzymes that are involved lateral and longitudinal elongation of the peptidoglycan. This neglects the presence of other transpeptidases that are present in the periplasm and also involved in remodeling and maturation of the peptidoglycan. It is therefore possible that if this was setting the speed limit for cell division, the simple expression of more transpeptidases may be sufficient to maintain the structural integrity of the cell wall.

## CELL ENVELOPE BIOSYNTHESIS



**Figure 3.** (A) Top panel shows an estimation for the number of ACP dehydratases necessary to form functional phospholipids, which is assumed to be a rate-limiting step on lipid synthesis. The rate of ACP dehydratases was inferred from experimental measurements via a stochastic kinetic model described in [Ruppe and Fox \(2018\)](#). Bottom panel shows the experimentally observed complex copy numbers using the stoichiometries  $[\text{FabA}]_2$  and  $[\text{FabZ}]_2$ . (B) An estimate for the number of peptidoglycan transpeptidases needed to complete maturation of the peptidoglycan. The mass of the murein monomer was estimated by approximating each amino acid in the pentapeptide chain as having a mass of 110 Da and each sugar in the disaccharide having a mass of 250 Da. The *in vivo* rate of transpeptidation in *E. coli* was taken from recent analysis by [Catherwood et al. \(2020\)](#). The bottom panel shows experimental measurements of the transpeptidase complexes in *E. coli* following the stoichiometries  $[\text{MrcA}]_2$ ,  $[\text{MrcB}]_2$ ,  $[\text{MrdA}]_1$ , and  $[\text{MrdB}]_1$ . Grey curves in each plot show the estimated number of complexes needed to satisfy the synthesis requirements scaled by the surface area as a function of growth rate.

259 **Energy Production**

260 Cells consume and generate energy predominantly in the form of nucleoside triphosphates (NTPs) in order to  
261 grow. The high-energy phosphodiester bonds of (primarily) ATP power a variety of cellular processes that drive  
262 biological systems away from thermodynamic equilibrium. We now turn to the synthesis of ATP as a potential  
263 process that may limit growth, which also requires us to consider the maintenance of the electrochemical proton  
264 gradient which powers it.

265 **ATP Synthesis**

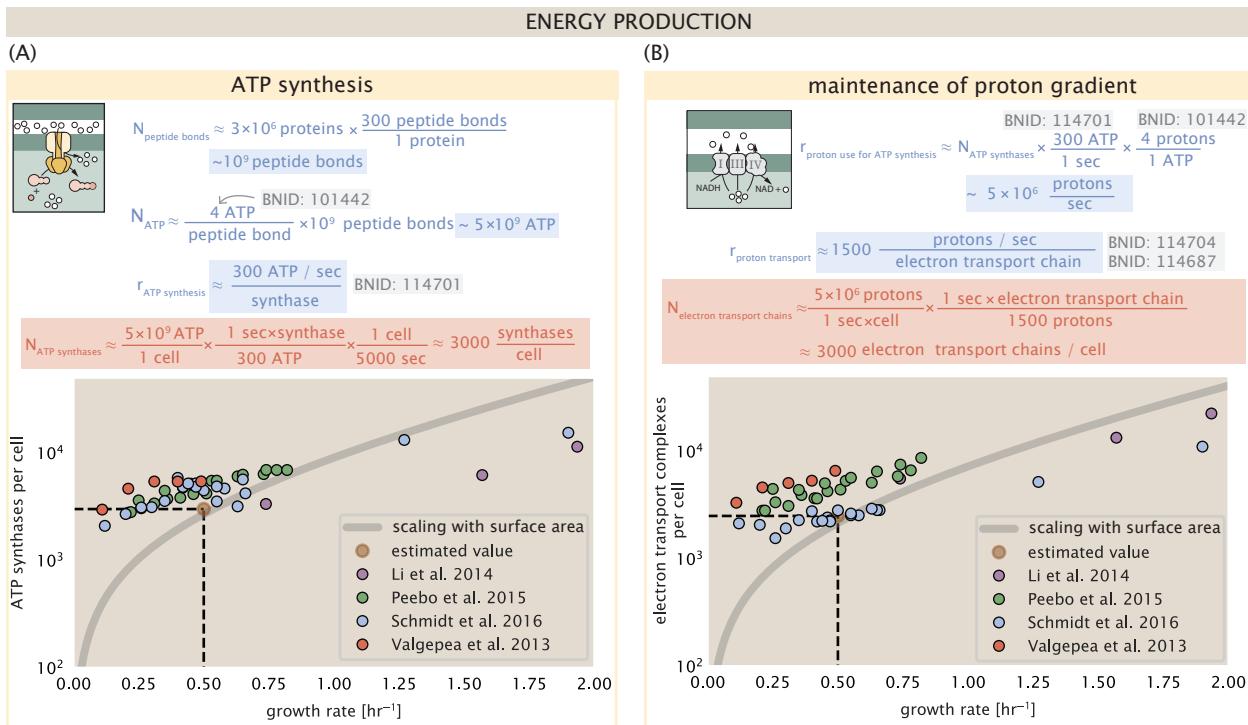
266 Hydrolysis of the terminal phosphodiester bond of ATP into ADP (or alternatively GTP and GDP) and an inorganic  
267 phosphate provides the thermodynamic driving force in a wide array of biochemical reactions. One such reaction  
268 is the formation of peptide bonds during translation, which requires  $\approx 2$  ATPs for the charging of an amino acid  
269 to the tRNA and  $\approx 2$  GTPs for the formation of each peptide bond. Assuming the ATP costs associated with error  
270 correction and post-translational modifications of proteins are negligible, we can make the approximation that  
271 each peptide bond has a net cost of  $\approx 4$  ATP (BNID: 101442). Formation of GTP from ATP is achieved via the action  
272 of nucleoside diphosphate kinase, which catalyzes this reaction without an energy investment (*Lascu and Gonin,*  
273 **2000**) and therefore consider all NTP requirements of the cell to be functionally equivalent to being exclusively  
274 ATP. In total, the energetic costs of peptide bond formation consume  $\approx 80\%$  of the cells ATP budget [BNID: 107782;  
275 106158; 101637; 111918, *Lynch and Marinov (2015); Stouthamer (1973)*]. The pool of ATP is produced by the F<sub>1</sub>-F<sub>0</sub>  
276 ATP synthase – a membrane-bound rotary motor which under ideal conditions can yield  $\approx 300$  ATP per second  
277 [BNID: 114701; *Weber and Senior (2003)*].

278 To estimate the total number of ATP equivalents consumed during a cell cycle, we will make the approximation  
279 that there are  $\approx 3 \times 10^6$  proteins per cell with an average protein length of  $\approx 300$  peptide bonds (BNID: 115702;  
280 108986; 104877). Taking these values together, coupled with an estimate of  $\approx 4$  ATP equivalents per peptide bond,  
281 we find that the typical *E. coli* cell consumes  $\sim 5 \times 10^9$  ATP per cell cycle on protein synthesis alone. Assuming that  
282 each ATP synthases operates at its maximal speed (300 ATP per second per synthase),  $\approx 3000$  ATP synthases  
283 are needed to keep up with the energy demands of the cell. This estimate is comparable with the experimental  
284 observations, shown in *Figure 4* (A). We note that this estimate assumes all ATP is synthesized via ATP synthase  
285 and neglects synthesis via fermentative metabolism. This simplification may explain why at the fastest growth  
286 rates ( $\approx 2 \text{ hr}^{-1}$ ), our continuum estimate predicts more synthase than is experimentally observed (gray line in  
287 *Figure 4*). At rapid growth rates, *E. coli* enters a type of overflow metabolism where fermentative metabolism  
288 becomes pronounced (*Szenk et al., 2017*).

289 **Generating the Proton Electrochemical Gradient**

290 In order to produce ATP, the F<sub>1</sub>-F<sub>0</sub> ATP synthase itself must consume energy. Rather than burning through its own  
291 product (and violating thermodynamics), this intricate macromolecular machine has evolved to exploit the elec-  
292 trochemical potential established across the inner membrane through cellular respiration. This electrochemical  
293 gradient is manifest by the pumping of protons into the intermembrane space via the electron transport chains  
294 as they reduce NADH. In *E. coli*, this potential difference is  $\approx -200$  mV (BNID: 102120). A simple estimate of the  
295 inner membrane as a capacitor with a working voltage of -200 mV reveals that  $\approx 2 \times 10^4$  protons must be present  
296 in the intermembrane space. However, each rotation of an ATP synthase shuttles  $\approx 4$  protons into the cytosol  
297 (BNID: 103390). With a few thousand ATP synthases producing ATP at their maximal rate, the potential difference  
298 would be rapidly abolished in a few milliseconds if it were not being actively maintained.

299 The electrochemistry of the electron transport complexes of *E. coli* have been the subject of intense biochemical  
300 and biophysical study (*Ingledew and Poole, 1984; Khademian and Imlay, 2017; Cox et al., 1970; Henkel et al., 2014*).  
301 A recent work (*Szenk et al., 2017*) examined the respiratory capacity of the *E. coli* electron transport complexes  
302 using structural and biochemical data, revealing that each electron transport chain rapidly pumps protons into  
303 the intermembrane space at a rate of  $\approx 1500$  protons per second (BIND: 114704; 114687). Using our estimate  
304 of the number of ATP synthases required per cell [*Figure 4(A)*], coupled with these recent measurements, we  
305 estimate that  $\approx 3000$  electron transport complexes would be necessary to facilitate the  $\sim 5 \times 10^6$  protons per  
306 second diet of the cellular ATP synthases. This estimate is in agreement with the number of complexes identified



**Figure 4. The abundance of F<sub>1</sub>-F<sub>0</sub> ATP synthases and electron transport chain complexes as a function of growth rate.**

(A) Estimate of the number of F<sub>1</sub>-F<sub>0</sub> ATP synthase complexes needed to accommodate peptide bond formation and other NTP dependent processes. Points in plot correspond to the mean number of complete F<sub>1</sub>-F<sub>0</sub> ATP synthase complexes that can be formed given proteomic measurements and the subunit stoichiometry [AtpE]<sub>10</sub>[AtpF]<sub>2</sub>[AtpB][AtpC][AtpH][AtpA]<sub>3</sub>[AtpG][AtpD]<sub>3</sub>. (B) Estimate of the number of electron transport chain complexes needed to maintain a membrane potential of -200 mV given estimate of number of F<sub>1</sub>-F<sub>0</sub> ATP synthases from (A). Points in plot correspond to the average number of complexes identified as being involved in aerobic respiration by the Gene Ontology identifier GO:0019646 that could be formed given proteomic observations. These complexes include cytochromes *bd1* ([CydA][CydB][CydX][CydH]), *bdII* ([AppC][AppB]), *bo<sub>3</sub>*,([CyoD][CyoA][CyoB][CyoC]) and NADH:quinone oxioreductase I ([NuoA][NuoH][NuoJ][NuoK][NuoL][NuoM][NuoN][NuoB][NuoC][NuoE][NuoF][NuoG][NuoI]) and II ([Ndh]). Grey lines in both (A) and (B) correspond to the estimate procedure described, but applied to a continuum of growth rates. We direct the reader to the Supporting Information for a more thorough description of this approach.

in the proteomic datasets [plot in **Figure 4(B)**]. This suggests that every ATP synthase must be accompanied by  $\approx 1$  functional electron transport chain.

### Limits on Biosynthesis in a Crowded Membrane

Our estimates thus far have focused on biochemistry at the periphery of the cell. Since surface area and volume do not scale identically as cell size changes, in order to better understand the physical constraints on transport and energy production it is necessary to consider the consequence of a changing S/V ratio, which will decrease at faster growth rates. Here we use our analysis of ATP production to consider this constraint.

In our estimate of ATP production above we found that a cell demands about  $5 \times 10^9$  ATP per cell cycle or  $10^6$  ATP/s. With a cell volume of roughly 1 fL (BNID: 100004), this corresponds to about  $2 \times 10^{10}$  ATP per fL of cell volume, in line with previous estimates (**Stouthamer and Bettenhausen, 1977; Szenk et al., 2017**). In **Figure 5(A)** we plot this ATP demand as a function of the S/V ratio in green, where we have considered a range of cell shapes from spherical to rod-shaped with an aspect ratio (length/width) equal to 4. In order to consider the maximum ATP that could be produced, we consider the amount of ATP that can be generated by a membrane filled with ATP synthase and electron transport complexes and a maximal production rate of about 3 ATP / (nm<sup>2</sup>·s) (**Szenk et al., 2017**). This is shown in blue in **Figure 5(A)**, which shows that at least for the growth rates observed (right column in plot), the energy demand is roughly an order of magnitude less. Interestingly, **Szenk et al. (2017)** found that ATP production by respiration is less efficient than by fermentation on a per membrane area basis, due to

324 the additional proteins of the electron transport chain. This suggests that, even under anaerobic growth, cells will  
325 have sufficient membrane space for ATP production.

326 The analysis highlights that there will indeed be a maximum attainable cell size due to a diminishing capacity  
327 to provide resources as the cell increases in size. The maximum energy production in *Figure 5(A)*, however, does  
328 represent a somewhat unachievable limit since the inner membrane must also include other proteins such as  
329 those we've considered for nutrient transport and cell wall biogenesis. To better understand the overall proteomic  
330 makeup of the inner membrane, we therefore used Gene Ontology (GO) annotations (*Ashburner et al., 2000*;  
331 *The Gene Ontology Consortium, 2018*) to identify all proteins embedded or peripheral to the inner membrane  
332 (GO term: 0005886). Those associated but not membrane-bound include proteins like MreB and FtsZ and must  
333 nonetheless be considered as a vital component occupying space on the membrane. In *Figure 5(B)*, we find that the  
334 total protein mass per  $\mu\text{m}^2$  is nearly constant across growth rates. Interestingly, when we consider the distribution  
335 of proteins grouped by their Clusters of Orthologous Groups (COG) (*Tatusov et al., 2000*), the relative abundance  
336 for those in metabolism (including ATP synthesis via respiration) is also relatively constant across growth rates,  
337 suggesting that no one process (energy production, nutrient uptake, etc.) is particularly dominating even at fast  
338 growth rates [*Figure 5(C)*].

### 339 Processes of the Central Dogma

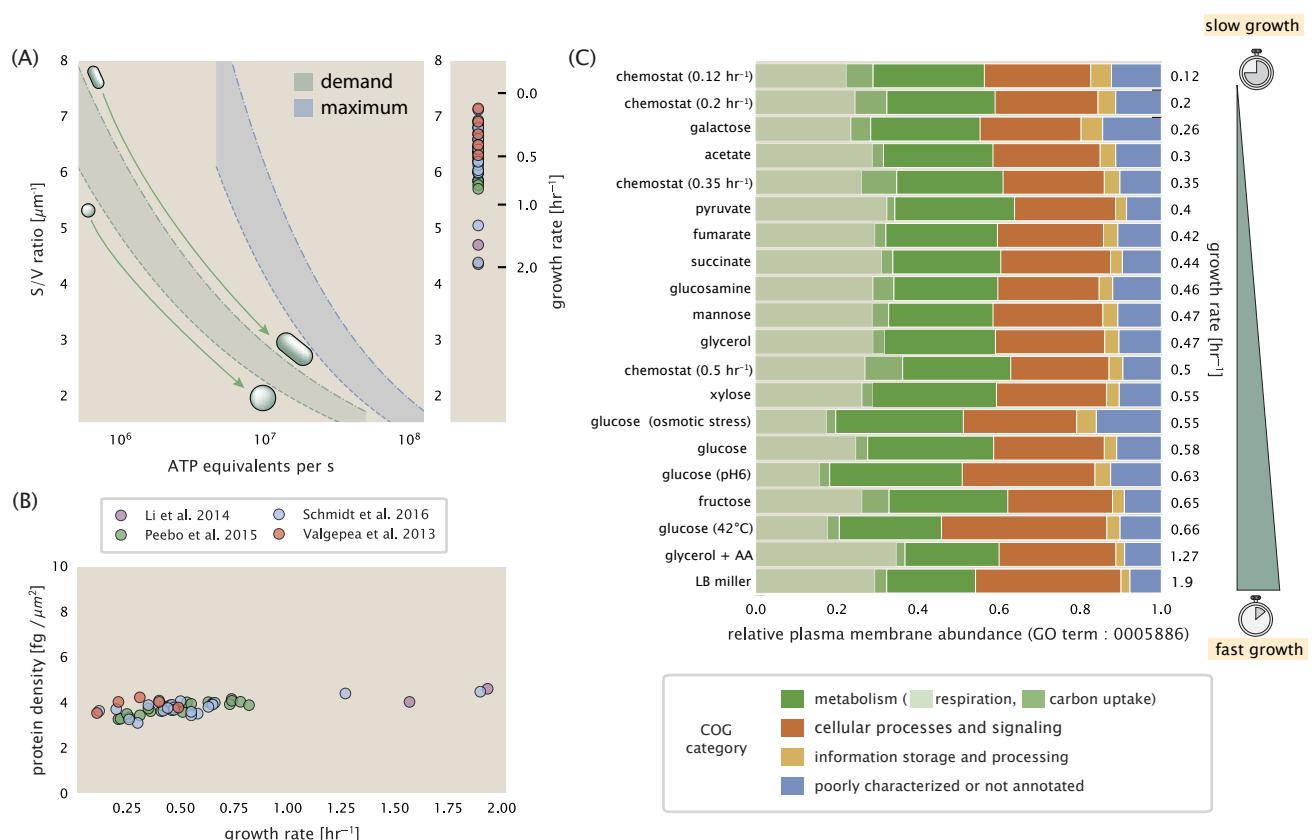
340 Up to this point, we have considered a variety of transport and biosynthetic processes that are critical to acquiring  
341 and generating new cell mass. While there are of course many other metabolic processes we could consider, we  
342 now turn our focus to some of the most central processes which *must* be undertaken irrespective of the growth  
343 conditions – those of the central dogma.

#### 344 DNA Replication

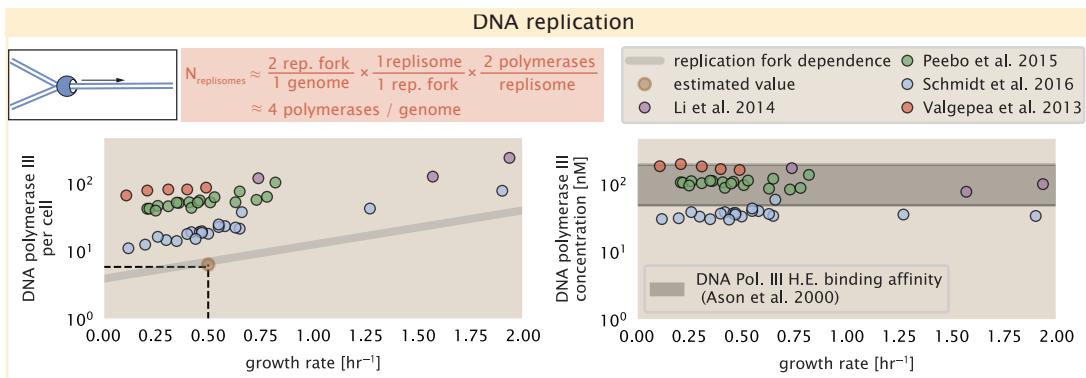
345 Most bacteria (including *E. coli*) harbor a single, circular chromosome and can have extra-chromosomal plasmids  
346 up to  $\sim 100$  kbp in length. While we consider the starting material dNTPs in *Figure 6-Figure Supplement 1* and dis-  
347 cussed further in the Appendix Section "Additional Process of the Central Dogma", here we focus our quantitative  
348 thinking on the chromosome of *E. coli*, which harbors  $\approx 5000$  genes and  $\approx 5 \times 10^6$  base pairs.

349 To successfully divide and produce viable progeny, this chromosome must be faithfully replicated and segre-  
350 gated into each nascent cell. Replication is initiated at a single region of the chromosome termed the *oriC* locus  
351 where a pair of replisomes, each consisting of two DNA polymerase III, begin their high-fidelity replication of the  
352 genome in opposite directions (*Fijalkowska et al., 2012*). *In vitro* measurements have shown that DNA Polymerase  
353 III copies DNA at a rate of  $\approx 600$  nucleotides per second (BNID: 104120). Therefore, to replicate a single chromo-  
354 some, two replisomes moving at their maximal rate would copy the entire genome in  $\approx 4000$  s. Thus, with a  
355 division time of 5000 seconds, there is sufficient time for a pair of replisomes complexes to replicate the entire  
356 genome.

357 In rapidly growing cultures, bacteria like *E. coli* can initiate as many as 10 - 12 replication forks at a given time  
358 (*Bremer and Dennis, 2008; Si et al., 2017*), we expect only a few DNA polymerases ( $\approx 10$ ) are needed. However,  
359 as shown in *Figure 6*, DNA polymerase III is nearly an order of magnitude more abundant. This discrepancy can  
360 be understood by considering its binding constant to DNA. *In vitro* characterization has quantified the  $K_D$  of DNA  
361 polymerase III holoenzyme to single-stranded and double-stranded DNA to be 50 and 200 nM, respectively (*Ason  
362 et al., 2000*). The right-hand plot in *Figure 6* shows that the concentration of DNA polymerase III across all data sets  
363 is within this range. Thus, its copy number appears to vary such that its concentration is approximately equal to the  
364 dissociation constant to the DNA. While the processes regulating the initiation of DNA replication are complex and  
365 involve more than just the holoenzyme, these data indicate that the kinetics of replication rather than the explicit  
366 copy number of the DNA polymerase III holoenzyme is the more relevant feature of DNA replication to consider.  
367 In light of this, the data in *Figure 6* suggests that for bacteria like *E. coli*, DNA replication does not represent a rate-  
368 limiting step in cell division. However, it is worth noting that for bacterium like *C. crescentus* whose chromosomal  
369 replication is initiated only once per cell cycle (*Jensen et al., 2001*), the time to double their chromosome indeed  
370 represents an upper limit to their growth rate.



**Figure 5. Influence of cell size and S/V ratio on ATP production and inner membrane composition.** (A) Scaling of ATP demand and maximum ATP production as a function of S/V ratio. Cell volumes of 0.5 fL to 50 fL were considered, with the dashed (—) line corresponding to a sphere and the dash-dot line (—·—) reflecting a rod-shaped bacterium like *E. coli* with a typical aspect ratio (length / width) of 4 (Shi et al., 2018). Approximately 50% of the bacterial inner membrane is assumed to be protein, with the remainder lipid. The right plot shows the measured growth rates, and their estimated S/V ratio using growth rate dependent size measurements from Si et al. (2017) (See Appendix Estimation of Cell Size and Surface Area on calculation). (B) Total protein mass per  $\mu\text{m}^2$  calculated for proteins with inner membrane annotation (GO term: 0005886). (C) Relative protein abundances by mass based on COG annotation. Metabolic proteins are further separated into respiration ( $F_1$ - $F_0$  ATP synthase, NADH dehydrogenase I, succinate:quinone oxidoreductase, cytochrome  $bo_3$  ubiquinol oxidase, cytochrome bd-ubiquinol oxidase) and carbohydrate transport (GO term: GO:0008643). Note that the elongation factor EF-Tu can also associate with the inner membrane, but was excluded in this analysis due to its high relative abundance (roughly identical to the summed protein shown in part (B)).



**Figure 6. Complex abundance estimates for dNTP synthesis and DNA replication.** An estimate for the minimum number of DNA polymerase holoenzyme complexes needed to facilitate replication of a single genome. Points in the left-hand plot correspond to the total number of DNA polymerase III holoenzyme complexes ( $[DnaE]_3[DnaQ]_3[HolE]_3[DnaX]_5[HolB][HolA][DnaN]_4[HolC]_4[Hold]_4$ ) per cell. Right-hand plot shows the effective concentration of DNA polymerase III holoenzyme (See Appendix Estimation of Cell Size and Surface Area for calculation of cell size). Grey lines in left-hand panel show the estimated number of complexes needed as a function of growth, the details of which are described in the Supplemental Information.

**Figure 6-Figure supplement 1.** Estimate and observations of the abundance of ribonucleotide reductase, a key component in dNTP synthesis.

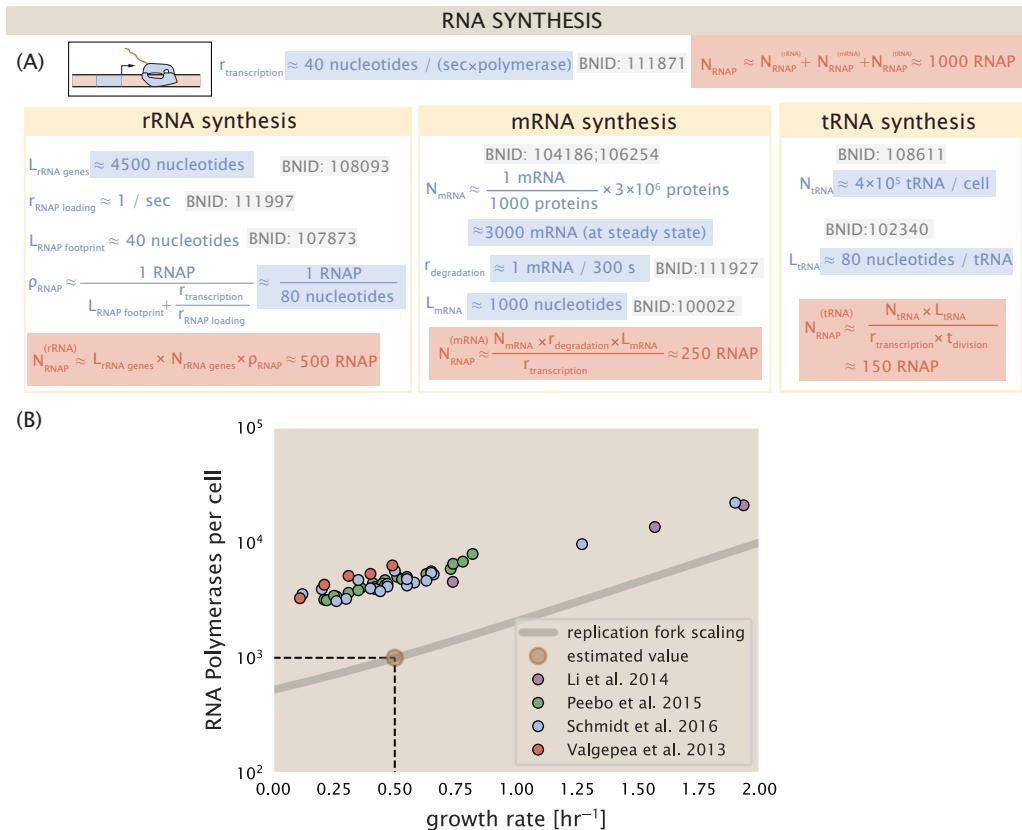
## 371 RNA Synthesis

372 We now turn our attention to the next stage of the central dogma – the transcription of DNA to form RNA. We  
 373 consider three major groupings of RNA, namely the RNA associated with ribosomes (rRNA), the RNA encoding the  
 374 amino-acid sequence of proteins (mRNA), and the RNA which links codon sequence to amino-acid identity during  
 375 translation (tRNA).

376 rRNA serves as the catalytic and structural component of the ribosome, comprising approximately 2/3 of the total  
 377 ribosomal mass, and is decorated with  $\approx 50$  ribosomal proteins. Each ribosome contains three rRNA molecules  
 378 of lengths 120, 1542, and 2904 nucleotides (BNID: 108093), meaning each ribosome contains  $\approx 4500$  nucleotides  
 379 overall. *In vivo* measurements of the kinetics of rRNA transcription have revealed that RNA polymerases are loaded  
 380 onto the promoter of an rRNA gene at a rate of  $\approx 1$  per second (BNID: 111997, 102362). If RNA polymerases are  
 381 constantly loaded at this rate, then we can assume that  $\approx 1$  functional rRNA unit is synthesized per second per  
 382 rRNA operon. While *E. coli* possesses 7 of these operons per chromosome, the fact that chromosome replication  
 383 can be parallelized means that the average dosage of rRNA genes can be substantially higher (up to  $\approx 70$  copies)  
 384 at fast growth rates (Dennis et al., 2004). At a growth rate of  $\approx 0.5$  hr<sup>-1</sup>, however, the average cell has  $\approx 1$  copy  
 385 of its chromosome and therefore approximately  $\approx 7$  copies of the rRNA operons, producing  $\approx 7$  rRNA units per  
 386 second. With a 5000 second division time, this means the cell is able to generate around  $3 \times 10^4$  functional rRNA  
 387 units, comparable within an order of magnitude to the number of ribosomes per cell.

388 How many RNA polymerases are then needed to constantly transcribe the required rRNA? If one polymerase is  
 389 loaded per second, and the transcription rate is  $\approx 40$  nucleotides per second (BNID: 101094), then the typical  
 390 spacing between polymerases will be  $\approx 40$  nucleotides. However, we must note that the polymerase itself has a  
 391 footprint of  $\approx 40$  nucleotides (BNID: 107873), meaning that one could expect to find one RNA polymerase per 80  
 392 nucleotide stretch of an rRNA gene. With a total length of  $\approx 4500$  nucleotides per operon and 7 operons per cell,  
 393 the number of RNA polymerases transcribing rRNA at any given time is then  $\approx 500$  per cell.

394 As outlined in **Figure 7**, and discussed further in the Appendix Section "Additional Process of the Central Dogma",  
 395 synthesis of mRNA and tRNA together require on the order of  $\approx 400$  RNAP. Thus, in total, one would expect  
 396 the typical cell to require  $\approx 1000$  RNAP to satisfy its transcriptional demands. As is revealed in **Figure 7(B)**, this  
 397 estimate is about an order of magnitude below the observed number of RNA polymerase complexes per cell ( $\approx$   
 398 5000 - 7000). The difference between the estimated number of RNA polymerase needed for transcription and  
 399 these observations, however, are consistent with recent literature revealing that  $\approx 80$  % of RNA polymerases in *E.*  
 400 *coli* are not transcriptionally active (Patrick et al., 2015).



**Figure 7. Estimation of the RNA polymerase demand and comparison with experimental data.** (A) Estimations for the number of RNA polymerase needed to synthesize sufficient quantities of rRNA, mRNA, and tRNA from left to right, respectively. (B) The RNA polymerase core enzyme copy number as a function of growth rate. Colored points correspond to the average number RNA polymerase core enzymes that could be formed given a subunit stoichiometry of  $[RpoA]_2[RpoC][RpoB]$ .

**Figure 7–Figure supplement 1.** Abundance and growth rate dependence of  $\sigma$ -70.

Our estimates also neglect other mechanistic features of transcription and transcriptional initiation more broadly. For example, we acknowledge that some fraction of the RNAP pool is nonspecifically bound to DNA during its search for promoters from which to begin transcription. Furthermore, we ignore the obstacles that RNA polymerase and DNA polymerase present to each other as they move along the DNA (Finkelstein and Greene, 2013). Additionally, while they represent the core machinery for transcription, RNA polymerase is not sufficient to initiate transcription. Initiation of transcription is dependent on the presence of  $\sigma$ -factors, protein cofactors that bind directly to the polymerase (Browning and Busby, 2016) and aid in promoter recognition. In **Figure 7–Figure Supplement 1**, we show that the predicted RNA polymerase copy number indeed is more comparable with the abundance of  $\sigma$ -70 (RpoD), the primary sigma factor in *E. coli*. There therefore remains more to be investigated as to what sets the observed abundance of RNA polymerase in these proteomic data sets. However, we conclude that the observed RNA polymerase abundances are generally in excess of what appears to be needed for growth, suggesting that the synthesis of RNA polymerase themselves are not particularly limiting.

#### 413 Protein Synthesis

We conclude our dialogue between back-of-the-envelope estimates and comparison with the proteomic data by examining the final process in the central dogma – translation. In doing so, we will begin with an estimate of the number of ribosomes needed to replicate the cellular proteome. While the rate at which ribosomes translate is well known to be dependent on the growth rate (Dai et al. (2018), a phenomenon we consider later in this work) we will make the approximation that translation occurs at a modest rate of  $\approx 15$  amino acids per second per ribosome (BNID: 100233) Under this approximation and our previous estimate of  $10^9$  peptide bonds per cell at a growth rate of  $0.5 \text{ hr}^{-1}$ , we can easily arrive at an estimate of  $\approx 10^4$  ribosomes needed per cell to replicate the entire protein

421 mass (**Figure 8(A)**, top). This point estimate, as well as the corresponding estimate across a continuum of growth  
422 rates, proves to be notably comparable to the experimental observations, shown in the bottom panel of **Figure 8(A)**.  
423 While the ribosome is responsible for the formation of peptide bonds, we do not diminish the importance of  
424 charging tRNAs with their appropriate amino acid, a process which occurs with remarkable fidelity. In the Appendix  
425 and in **Figure 8–Figure Supplement 1**, we consider the process of ligating tRNAs to their corresponding amino acid  
426 and again find notable accord between the data and our quantitative expectations.

427 Having completed our circuit through key processes of cellular growth outlined in **Figure 1**, we can now take  
428 stock of our understanding of the observed growth rate dependence and abundances of various protein com-  
429 plexes. We note that, broadly speaking, these simple estimates have been reasonably successful in quantitatively  
430 describing the observations in the proteomic data, suggesting that the proteome is tuned in composition and  
431 absolute abundance to match the growth rate requirements without any one process representing a singular bot-  
432 tleneck or rate limiting step in division. However, in our effort to identify key limitations on growth, there are two  
433 notable observations that we wish to emphasize.

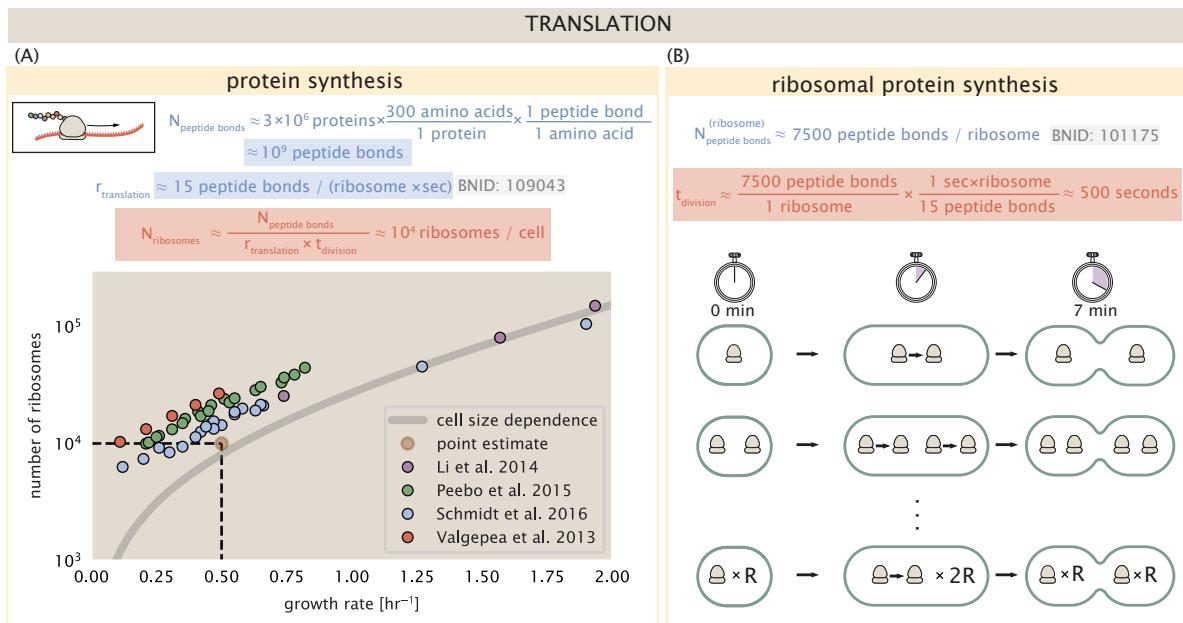
434 The first is a recurring theme throughout the estimates investigated here, which is that any inherent biochemical  
435 rate limitation can be overcome by expressing more proteins. We can view this as a parallelization of each  
436 biosynthesis task, which helps explain why bacteria tend to increase their protein content (and cell size) as growth  
437 rate increases (*Ojkic et al., 2019*). The second, and ultimately the most significant in defining the cellular growth  
438 rate, is that the synthesis of ribosomal proteins presents a special case where parallelization is *not* possible and  
439 thereby imposes a limit on the fastest possible growth rate. Each ribosome has  $\approx$  7500 amino acids across all of  
440 its protein components which must be strung together as peptide bonds through the action of another ribosome.  
441 Once again using a modest elongation rate of  $\approx$  15 amino acids per second, we arrive an estimate of  $\approx$  500 seconds  
442 or  $\approx$  7 minutes to replicate a single ribosome. This limit, as remarked upon by others (*Dill et al., 2011*), serves as a  
443 hard theoretical boundary for how quickly a bacterium like *E. coli* can replicate. As each ribosome would therefore  
444 need to copy itself, this 7 minute speed limit is independent of the number of ribosomes per cell [**Figure 8(B)**], yet  
445 assumes that the only proteins that need to be replicated for division to occur are ribosomal proteins, a regime  
446 not met in biological reality. This poses an optimization problem for the cell – how are the translational demands  
447 of the entire proteome met without investing resources in the production of an excess of ribosomes?

448 This question, more frequently presented as a question of optimal resource allocation, has been the target of  
449 an extensive dialogue between experiment and theory over the past decade. In a now seminal work, *Scott et al.*  
450 (2010) present an elegant treatment of resource allocation through partitioning of the proteome into sectors –  
451 one of which being ribosome-associated proteins whose relative size ultimately defines the total cellular growth  
452 rate. In more recent years, this view has been more thoroughly dissected experimentally (*Klumpp and Hwa, 2014*;  
453 *Basan et al., 2015; Dai et al., 2018, 2016; Erickson et al., 2017*) and together have led to a paradigm-shift in how we  
454 think of cellular physiology at the proteomic-level. However, the quantitative description of these observations is  
455 often couched in terms of phenomenological constants and effective parameters with the key observable features  
456 of expression often computed in relative, rather than absolute, abundances. Furthermore, these approaches  
457 often exclude or integrate away effects of cell size and chromosome content, which we have found through our  
458 estimates to have important connections to the observed cellular growth rate.

459 In the closing sections of this work, we explore how ribosomal content, total protein abundance, and chromo-  
460 somal replication are intertwined in their control over the cellular growth rate. To do so, we take a more careful  
461 view of ribosome abundance, increasing the sophistication of our analysis by exchanging our order-of-magnitude  
462 estimates for a minimal mathematical model of growth rate control. This is defined by parameters with tangible  
463 connections to the biological processes underlying cellular growth and protein synthesis. Using this model, we in-  
464 terrogate how the size of the ribosome pool and its corresponding translational capacity enable cells to maintain  
465 a balance between the of amino acids via metabolism and catabolism and their consumption through the peptide  
466 bond formation required for growth.

#### 467 **Maximum Growth Rate is Determined by the Ribosomal Mass Fraction**

468 The 7 minute speed limit shown in **Figure 8(B)** assumes all proteins in the cell are ribosomes. In order to connect  
469 this to the experimental data (and physiological reality more broadly), we first need to relax this assumption and  
470 determine a translation-limited growth rate. Here, we will assume that the cell is composed of  $N_{\text{pep}}$  peptide bonds



**Figure 8. Estimation of the required number of ribosomes and the speed limit for bacterial replication.** (A) Estimation of the number of ribosomes required to synthesize  $10^9$  peptide bonds with an elongation rate of 15 peptide bonds per second. The average abundance of ribosomes is plotted as a function of growth rate. Our estimated values are shown for a growth rate of  $0.5 \text{ hr}^{-1}$ . Grey lines correspond to the estimated complex abundance calculated at different growth rates. (B) Estimation for the time to replicate a ribosome. This rate is independent of the number of ribosomes  $R$  and instead is limited by the time required to double an individual ribosome.

**Figure 8-Figure supplement 1.** Estimate and observed abundance and growth rate dependence of tRNA ligases.

and  $R$  ribosomes, whose precise values will depend on the growth rate  $\lambda$ . The protein subunits of each ribosomal protein sum to a total of  $\approx 7500$  amino acids as noted earlier, which we denote by  $L_R$ . With an average mass of an amino acid of  $m_{\text{AA}} \approx 110 \text{ Da}$  (BNID: 104877), the total ribosomal mass fraction  $\Phi_R$  is given by

$$\Phi_R = \frac{m_{\text{ribosomes}}}{m_{\text{proteome}}} \approx \frac{m_{\text{AA}} \times R \times L_R}{m_{\text{AA}} \times N_{\text{pep}}} = \frac{R \times L_R}{N_{\text{pep}}}. \quad (1)$$

For exponentially growing cells (Godin et al., 2010), the rate of cellular growth will be related to the rate of protein synthesis via

$$\lambda N_{\text{pep}} = r_t \times R \times f_a, \quad (2)$$

where  $r_t$  is the translation rate. Here, we've introduced a multiplicative factor  $f_a$  which represents the fraction of the ribosomes that are actively translating. This term allows us to account for immature or non-functional ribosomes or active sequestration of ribosomes through the action of the secondary messenger alarmone (p)ppGpp in poorer nutrient conditions (Hauriyliuk et al., 2015).

Combining Equation 1 and Equation 2 results in an expression for a translation-limited growth rate, which is given by

$$\lambda_{\text{translation-limited}} = \frac{r_t \times \Phi_R \times f_a}{L_R}. \quad (3)$$

This result, derived in a similar manner in Klumpp et al. (2013), reflects mass-balance under steady state growth and has long provided a rationalization of the apparent linear increase in *E. coli*'s ribosomal content as a function growth rate (Maaløe, 1979; Dennis et al., 2004; Scott et al., 2010). The left-hand panel of Figure 9(A) shows this growth rate plotted as a function of the ribosomal mass fraction. In the regime where all ribosomes are active ( $f_a = 1$ ) and the entire proteome is composed of ribosomal proteins ( $\Phi_R = 1$ ), indeed, we arrive at the maximum theoretical growth rate of  $r_t/L_R$ , and  $\approx 7 \text{ min}$  for *E. coli*.

Connecting Equation 3 to the proteomic data serving as the centerpiece of our work, however, requires knowledge of  $f_a$  at each growth rate as proteomic measurements only provide a measure of  $\Phi_R$ . Recently, Dai et al.

490 (2016) determined  $f_a$  as a function of the growth rate (**Figure 9(A)**, right-hand panel, inset), revealing that  $f_a \approx 1$  at  
 491 growth rates above  $0.75 \text{ hr}^{-1}$  and  $f_a < 1$  as the growth rate slows. Using these data, we inferred the approximate  
 492 active fraction (see the Appendix Section "Calculation of active ribosomal fraction") at each growth rate and used  
 493 this to compute  $\Phi_R \times f_a$  (**Figure 9(A)**, colored points in right-hand panel). In general, these data skirt the translation-  
 494 limited growth rate determined using **Equation 3**, where we have taken  $r_t$  to be the maximal elongation rate of 17  
 495 amino acids per second measured by *Dai et al.* (2016). There is a notable discrepancy between the data collected  
 496 in *Schmidt et al.* (2016); *Li et al.* (2014) and that collected from *Valgepea et al.* (2013); *Peebo et al.* (2015). When  
 497 compared to other measurements (non-proteomic based) of the active ribosome mass fraction (**Figure 9(B)**, grey  
 498 points in right-hand panel), the data from *Valgepea et al.* (2013) and *Peebo et al.* (2015) are notably aberrant, sug-  
 499 gesting a systematic error in these data. These additional measurements come from a number of recent studies  
 500 and are determined from measurements of total RNA to total protein mass ratios (**Figure 9–Figure Supplement 1**).  
 501

502 Together, these results illustrate that the growth rates observed across the amalgamated data sets are close  
 503 to the translation-limited growth rate determined through ribosomal activity, at least for the data reported in  
 504 *Schmidt et al.* (2016) and *Li et al.* (2014). While this is a useful framework to consider how the relative abundance  
 505 of ribosomes (compared to all other proteins) defines the growth rate, it is worth noting that as growth rate  
 506 increases, so does the cell size and therefore so will the total proteomic mass (*Basan et al.*, 2015). With a handle  
 507 on how elongation rate and the total number of peptide bonds per proteome is related to the growth rate, we  
 508 now expand this description to account for the increasing cell size and ribosome copy number at faster growth  
 509 rates, enabling us to identify a potential bottleneck in the synthesis of rRNA.  
 510

## 509 rRNA Synthesis Presents a Potential Bottleneck During Rapid Growth

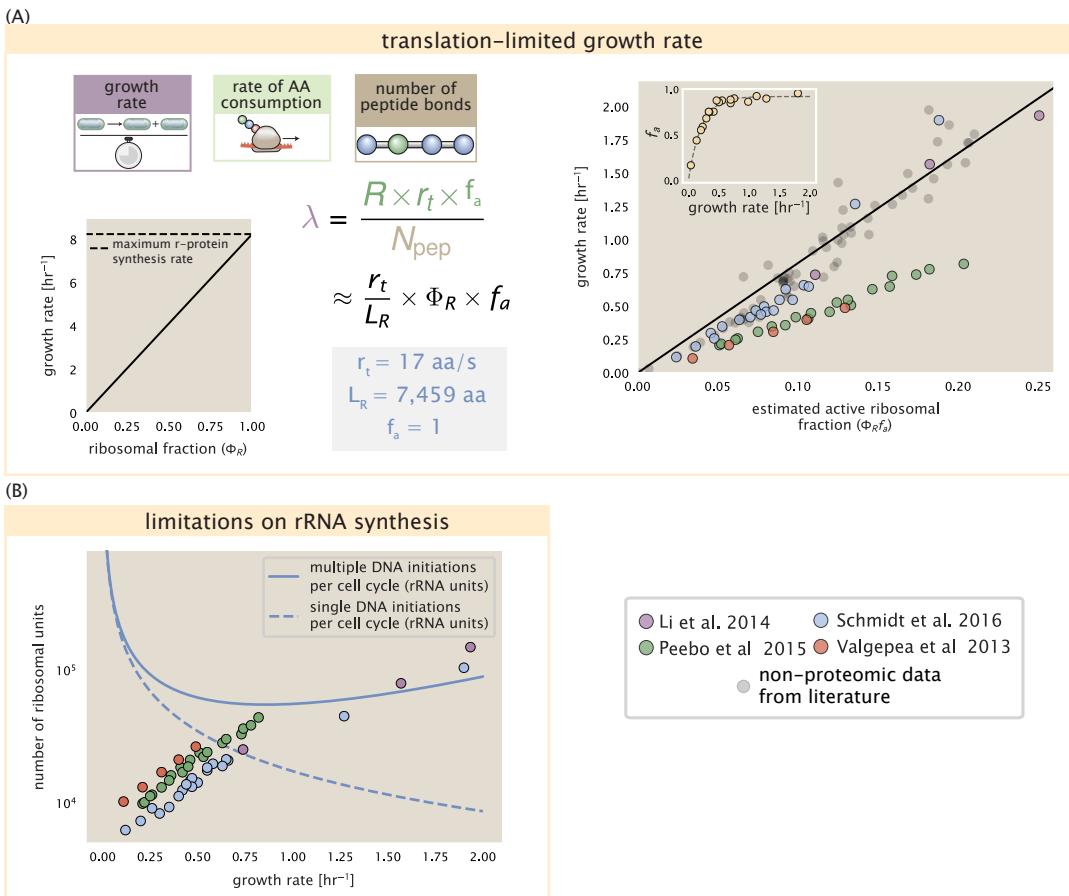
510 Even under idealized experimental conditions, *E. coli* rarely exhibits growth rates above  $2 \text{ hr}^{-1}$  (*Bremer and Dennis*,  
 511 2008), which is still well-below the synthesis rate of a single ribosome, and below the maximum growth rates  
 512 reported for several other bacteria (*Roller et al.*, 2016). While we have considered potential limits imposed by  
 513 translation of ribosomal proteins, here we consider potential limiting regimes specific to the synthesis of rRNA.  
 514

515 Due to multiple initiations of chromosomal replication per cell doubling, the effective number of rRNA operons  
 516 increases with growth rate and will do so in proportion to the average number of origins per cell,  $\langle \# \text{ ori} \rangle$ . This latter  
 517 parameter is set by how often replication must be initiated in order to keep up with cell doubling times  $\tau$ , whose  
 518 time may be shorter than the cell cycle time  $\tau_{\text{cyc}}$  (referring to the time from replication initiation to cell division)  
 519 (*Dennis et al.*, 2004). This is quantified by

$$\langle \# \text{ ori} \rangle = 2^{\tau_{\text{cyc}}/\tau} = 2^{\tau_{\text{cyc}} \lambda / \log(2)}. \quad (4)$$

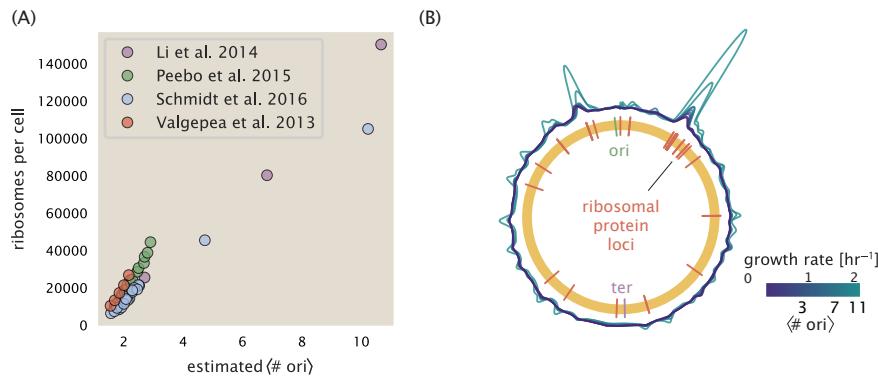
520 We used the experimental measurements of  $\tau_{\text{cyc}}$  (the timescale of chromosome replication and cell division) and  
 521  $\tau$  (the timescale of a cell doubling) from *Si et al.* (2017) (**Figure 9–Figure Supplement 1(B)**) to calculate  $\langle \# \text{ ori} \rangle$  with  
 522 **Equation 4** as a function of growth rates. For growth rates above about  $0.5 \text{ hr}^{-1}$ ,  $t_{\text{cyc}}$  is approximately constant  
 523 at about 70 minutes, implying that  $\langle \# \text{ ori} \rangle$  will grow exponentially with growth rates beyond  $0.5 \text{ hr}^{-1}$ . As the  
 524 rRNA operons are predominantly located close to origin of replication (BNID: 100352), we make the simplifying  
 525 assumption that that the number of rRNA operons will be directly proportional to  $\langle \# \text{ ori} \rangle$ .

526 Returning to our rule-of-thumb of 1 functional rRNA unit per second per transcribing operon, we estimate the  
 527 maximum number of ribosomes that could be made as a function of growth rate (**Figure 9(B)**, blue curve). Although  
 528 we expect this estimate to significantly overestimate rRNA abundance at slower growth rates ( $\lambda < 0.5 \text{ hr}^{-1}$ ), this  
 529 provides a useful reference alongside the proteomic measurements, particularly in the regime of fast growth. For  
 530 growth rates above about  $1 \text{ hr}^{-1}$ , for example, we find that cells will need to transcribe rRNA near their maximal  
 531 rate. As a counter example, if *E. coli* did not initiate multiple rounds of replication, but managed to replicate their  
 532 chromosome within the requisite time limit, they would be unable to make enough rRNA for the observed number  
 533 of ribosomes (dashed blue curve in **Figure 9(C)**). The convergence between the maximum rRNA production and  
 534 measured ribosome copy number suggests rRNA synthesis may begin to present a bottleneck at the fastest growth  
 535 rates due to the still-limited copies of rRNA genes.



**Figure 9. Translation-limited growth rate.** (A) *left:* Translation-limited growth as a function of the ribosomal fraction. The solid line is calculated for an elongation rate of 17 aa per second. The dashed line corresponds to the maximum rate of ribosomal protein synthesis ( $\approx 7$  min). *right:* Translation-limited growth rate as a function of the actively translating ribosomal fraction. The actively translating ribosomal fraction is calculated using the estimated values of  $f_a$  from [Dai et al. \(2016\)](#) (shown in inset; see Appendix Calculation of active ribosomal fraction for additional detail). Gray data points show additional measurements from literature and consider further in the supplemental figure part (A). (B) Maximum number of rRNA units that can be synthesized as a function of growth rate. Solid curve corresponding to the rRNA copy number is calculated by multiplying the number of rRNA operons by the estimated number of (# ori) at each growth rate. The quantity (# ori) was calculated using Equation 4 and the measurements from [Si et al. \(2017\)](#). The dashed line shows the maximal number of functional rRNA units produced from a single chromosomal initiation per cell cycle.

**Figure 9–Figure supplement 1.** Comparison of  $\Phi_R f_a$  with literature and estimation of (# ori).



**Figure 10. Cells increase both absolute ribosome abundance and  $\Phi_R$  with  $\langle \# \text{ori} \rangle$ .** (A) Plot of the ribosome copy number estimated from the proteomic data against the estimated  $\langle \# \text{ori} \rangle$  (see Appendix Estimation of  $\langle \# \text{ori} \rangle / \langle \# \text{ter} \rangle$  and  $\langle \# \text{ori} \rangle$  for additional details). (B) A running Gaussian average (20 kbp st. dev.) of protein copy number is calculated for each growth condition considered by (Schmidt et al., 2016) based on each gene's transcriptional start site. Since total protein abundance increases with growth rate, protein copy numbers are median-subtracted to allow comparison between growth conditions.  $\langle \# \text{ori} \rangle$  are estimated using the data in (A) and Equation 4.

### 535 Rapid Growth Requires *E. coli* to Increase Both Cell Size and Ribosomal Mass Fraction

536 In the right-hand side of Figure 9(B), we also find that above about  $0.75 \text{ hr}^{-1}$ , the growth rate is determined solely  
 537 by the ribosomal mass fraction  $\Phi_R$ , since  $f_a$  is close to 1, and  $r_i$  is near its maximal rate (Dai et al., 2016). While  $\Phi_R$   
 538 will need to increase in order for cells to grow faster, the fractional dependence in Equation 3 gives little insight  
 539 into how this scaling is actually achieved by the cell.

540 It is now well-documented that *E. coli* cells add a constant volume per origin of replication, which is robust  
 541 to a remarkable array of cellular perturbations (Si et al., 2017). Given the proteomic measurements featured in  
 542 this work, we find that the ribosome copy number also scales in proportion to  $\langle \# \text{ori} \rangle$  (Figure 10(A)). However, an  
 543 increase in ribosome abundance alone is not necessarily sufficient to increase growth rate and we also need to  
 544 consider how  $\Phi_R$  varies with  $\langle \# \text{ori} \rangle$ . Importantly, as shown in Figure 10(B), we find that the deviations in protein  
 545 expression with  $\langle \# \text{ori} \rangle$  are largely restricted to regions of ribosomal protein genes Figure 10(B). Here we have  
 546 calculated the position-dependent protein expression across the chromosome by a running Gaussian average of  
 547 protein copy number (20 kbp st. dev. averaging window) based on each gene's transcriptional start site. These  
 548 were median-subtracted to account for the change in total protein abundance with  $\langle \# \text{ori} \rangle$ . This result suggests  
 549 that  $\Phi_R$  is also being tuned in proportion to  $\langle \# \text{ori} \rangle$  under nutrient-limited growth, and in particular, it is through this  
 550 additional dependence on  $\Phi_R$ , combined with the exponential increase in  $\langle \# \text{ori} \rangle$ , that *E. coli* exhibits an exponential  
 551 increase in cell size with growth rate.

### 552 A Minimal Model of Nutrient-Mediated Growth Rate Control

553 While the preceding subsections highlight a dominant role for ribosomes in setting the growth rate, our analysis  
 554 on the whole emphasizes how the total proteomic content also changes in response to variable growth conditions  
 555 and growth rate. In this final section we use a minimal model of growth rate control to better understand how  
 556 this interconnection between ribosomal abundance and total protein abundance influences the observed growth  
 557 rate.

558 Here we propose that cells modulate their protein abundance in direct response to the availability of nutrients  
 559 in their environment. As noted earlier, bacteria can modulate ribosomal activity through the secondary messenger  
 560 molecules like (p)ppGpp in poorer nutrient conditions (Figure 9(C) - inset; Dai et al. (2016)). Importantly, these  
 561 secondary messengers also cause global changes in transcriptional and translational activity (Hauryliuk et al.,  
 562 2015; Zhu and Dai, 2019; Büke et al., 2020). In *E. coli*, amino acid starvation leads to the accumulation of de-  
 563 acylated tRNAs at the ribosome's A-site and a strong increase in (p)ppGpp synthesis activity by the enzyme RelA  
 564 (Hauryliuk et al., 2015). Along with this, there is increasing evidence that (p)ppGpp also acts to inhibit the initiation  
 565 of DNA replication (Kraemer et al., 2019), providing a potential mechanism for cells to lower  $\langle \# \text{ori} \rangle$  and maintain

566 a smaller cell size in poorer nutrient conditions (*Fernández-Coll et al., 2020*).

567 To consider this quantitatively, we assume that cells modulate their proteome ( $N_{\text{pep}}$ ,  $R$ ,  $\Phi_R$ ) to better maximize their rate of peptide elongation  $r_t$ . The elongation rate  $r_t$  will depend on how quickly the ribosomes can match codons with their correct amino-acyl tRNA, along with the subsequent steps of peptide bond formation and translocation. This ultimately depends on the cellular concentration of amino acids, which we treat as a single effective species,  $[AA]_{\text{eff}}$ . In our model, we determine the the rate of peptide elongation  $r_t$  and achievable growth rate as simply depending on the supply of amino acids (and, therefore, also amino-acyl tRNAs), through a parameter  $r_{AA}$  in units of AA per second, and the rate of amino acid consumption by protein synthesis ( $r_t \times R \times f_a$ ). This is shown schematically in *Figure 11(A)* and derived in the Appendix Section "Derivation of Minimal Model for Nutrient-Mediated Growth Rate Control". Given our observation that protein synthesis and energy production are not limiting, we assume that other molecular players required by ribosomes such as elongation factors and GTP are available in sufficient abundance.

578 In *Figure 11(B)*, we illustrate how the elongation rate will depend on the ribosomal copy number. Here, we  
579 have considered an arbitrarily chosen  $r_{AA} = 5 \times 10^6 \text{ AA} \cdot \text{s}^{-1} \cdot \mu\text{m}^{-3}$  and  $f_a = 1$  for a unit cell volume  $V = 1\text{fL}$  (we  
580 provide the interactive figure *Figure 11–Figure Supplement 1* which allows the user to explore different regimes  
581 of this parameter space). At low ribosome copy numbers, the observed elongation rate is dependent primarily on  
582  $[AA]_{\text{eff}}$  through  $r_{AA}$  [as  $r_t^{\max} \times R \times f_a \ll r_{AA}$ , point (1) in *Figure 11(B)*]. As the ribosome copy number is increased  
583 such that the amino acid supply rate and consumption rate are nearly equal [point (2) in *Figure 11(B)*], the ob-  
584 served elongation rate begins to decrease sharply. When the ribosome copy number is increased even further,  
585 consumption at the maximum elongation rate exceeds the supply rate, yielding a significantly reduced elongation  
586 rate [point (3) in *Figure 11B*]. While the elongation rate will always be dominated by the amino acid supply rate  
587 at sufficiently low ribosome copy numbers, the elongation rate at larger ribosome abundances can be increased  
588 by tuning  $f_a$  such that not all ribosomes are elongating, reducing their total consumption rate.

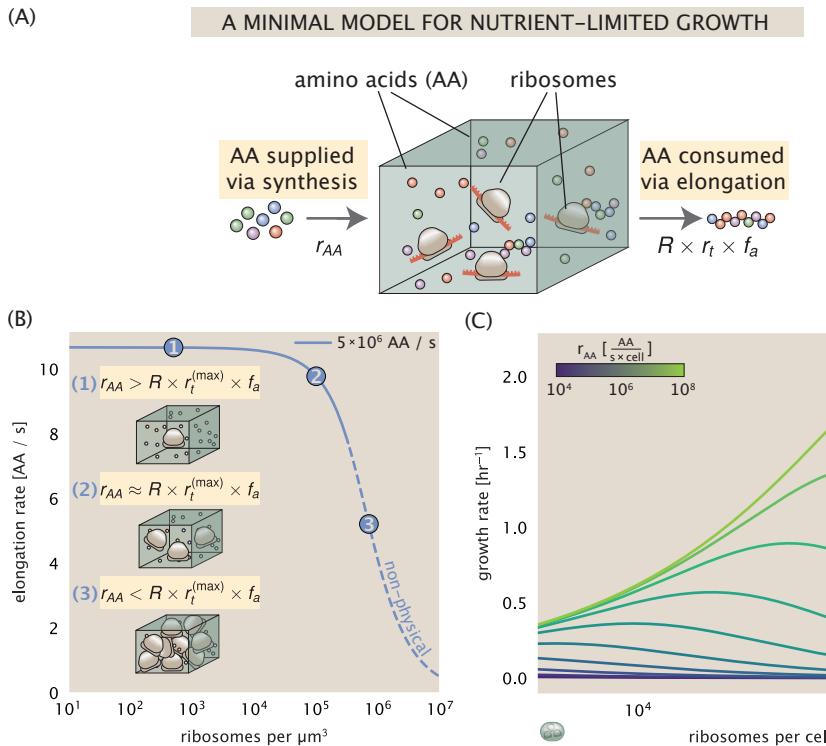
## 589 Optimal Ribosomal Content and Cell Size Depend on Nutrient Availability and Metabolic Capacity

590 To relate elongation rate to growth rate, we constrain the set of parameters based on our available proteomic mea-  
591 surements; namely, we restrict the values of  $R$ ,  $N_{\text{pep}}$ , and cell size  $V$  to those associated with the amalgamated  
592 proteomic data (described in the Appendix Section "Estimation of Total Protein Content per Cell"). We then con-  
593 sider how changes in the nutrient conditions, through the parameter  $r_{AA}$ , influence the maximum growth rate as  
594 determined by *Equation 3*. *Figure 11(C)* shows how the growth rate depends on the rate of amino acid supply  $r_{AA}$   
595 as a function of the cellular ribosome copy number. A feature immediately apparent is the presence of a maximal  
596 growth rate whose dependence on  $R$  (and consequently, the cell size) increases with increasing  $r_{AA}$ . Importantly,  
597 however, there is an optimum set of  $R$ ,  $N_{\text{pep}}$ , and  $V$  that are strictly dependent on the value of  $r_{AA}$ . This shows that  
598 increasing the ribosomal concentration beyond the cell's metabolic capacity will have the adverse consequence  
599 of depleting the supply of amino acids and a concomitant decrease in the elongation rate  $r_t$  (*Figure 11(B)*) and  
600 growth rate.

601 Also of note is the growth rate trends observed at low values of  $r_{AA}$  [purple and blue lines in *Figure 11(C)*],  
602 representative of growth in nutrient-poor media. In these conditions, there no longer exists a peak in growth, at  
603 least within the range of physiologically-relevant ribosome copy numbers. This is a regime, associated with slower  
604 growth rates, where cells limit their pool of actively translating ribosomes by decreasing  $f_a$  (*Dai et al., 2016*), which  
605 we find would help maintain the pool of available amino acids  $[AA]_{\text{eff}}$  and increase the achievable elongation rate.

## 606 Discussion

607 Continued experimental and technological improvements have led to a treasure trove of quantitative biological  
608 data (*Hui et al., 2015; Schmidt et al., 2016; Si et al., 2017; Gallagher et al., 2020; Peebo et al., 2015; Valgepea et al.,*  
609 *2013*), and an ever advancing molecular view and mechanistic understanding of the constituents that support  
610 bacterial growth (*Taheri-Araghi et al., 2015; Morgenstein et al., 2015; Si et al., 2019; Karr et al., 2012; Kostinski and*  
611 *Reveni, 2020*). In this work we have compiled what we believe to be the state-of-the-art knowledge on proteomic  
612 copy number across a broad range of growth conditions in *E. coli*. We have made this data accessible through a  
613 [GitHub repository](#), and an [interactive figure](#) that allows exploration of specific protein and protein complex copy  
614 numbers. Through a series of order-of-magnitude estimates that traverse key steps in the bacterial cell cycle, this



**Figure 11. A minimal model of growth rate control under nutrient limitation.** (A) We consider a unit volume of cellular material composed of amino acids (colored spheres) provided at a supply rate  $r_{AA}$ . These amino acids are polymerized by a pool of ribosomes (brown blobs) at a rate  $r_t \times R \times f_a$ , where  $r_t$  is the elongation rate,  $R$  is the ribosome copy number in the unit volume, and  $f_a$  is the fraction of those ribosomes actively translating. (B) The observed elongation rate is plotted as a function of ribosomes. The three points correspond to three regimes of ribosome copy numbers and are shown schematically on the left-hand side. The region of the curve shown as dashed lines represents a non-physical copy number, but is shown for illustrative purposes. This curve was generated using an amino acid supply rate of  $5 \times 10^6$  AA / s, a maximal elongation rate of 17.1 AA / s,  $f_a = 1$ , and a unit cell volume of  $V = 1$  fL. See Appendix Derivation of Minimal Model for Nutrient-Mediated Growth Rate Control for additional model details. (C) The cellular growth rate is plotted as a function of total cellular ribosome copy number for different cellular amino acid supply rates, with blue and green curves corresponding to low and high supply rates, respectively. As the ribosome copy number is increased, so too is the cell size and total protein abundance  $N_{pep}$ . We direct the reader to the Supplemental Information for discussion on the inference of the relationship between cell size, number of peptide bonds, and ribosome copy number.

**Figure 11–Figure supplement 1.** An interactive figure for exploration of the model parameter space.

615 proteomic data has been a resource to guide our understanding of two key questions: what biological processes  
616 limit the absolute speed limit of bacterial growth, and how do cells alter their molecular constituents as a function  
617 of changes in growth rate or nutrient availability? While not exhaustive, our series of estimates provide insight  
618 on the scales of macromolecular complex abundance across four classes of cellular processes – the transport of  
619 nutrients, the production of energy, the synthesis of the membrane and cell wall, and the numerous steps of the  
620 central dogma.

621 In general, the copy numbers of the complexes involved in these processes were in reasonable agreement  
622 with our order-of-magnitude estimates. Since many of these estimates represent soft lower-bound quantities, this  
623 suggests that cells do not express proteins grossly in excess of what is needed for a particular growth rate. Several  
624 exceptions, however, also highlight the dichotomy between a proteome that appears to "optimize" expression  
625 according to growth rate and one that must be able to quickly adapt to environments of different nutritional quality.  
626 Take, for example, the expression of carbon transporters. Shown in *Figure 2(B)*, we find that cells always express  
627 a similar number of glucose transporters irrespective of growth condition. At the same time, it is interesting to  
628 note that many of the alternative carbon transporters are still expressed in low but non-zero numbers ( $\approx 10$ -  
629 100 copies per cell) across growth conditions. This may relate to the regulatory configuration for many of these  
630 operons, which require the presence of a metabolite signal in order for alternative carbon utilization operons to  
631 be induced (Monod, 1949; Laxhuber et al., 2020). Furthermore, upon induction, these transporters are expressed  
632 and present in abundances in close agreement with a simple estimate.

633 Of the processes illustrated in *Figure 1*, we arrive at a ribosome-centric view of cellular growth rate control.  
634 This is in some sense unsurprising given the long-held observation that *E. coli* and many other organisms vary  
635 their ribosomal abundance as a function of growth conditions and growth rate (Scott et al., 2010; Metzl-Raz et al.,  
636 2017). However, through our dialogue with the proteomic data, two additional key points emerge. The first relates  
637 to our question of what process sets the absolute speed limit of bacterial growth. While a cell can parallelize  
638 many of its processes simply by increasing the abundance of specific proteins or firing multiple rounds of DNA  
639 replication, this is not so for synthesis of ribosomes [*Figure 9(A)*]. The translation time for each ribosome [ $\approx 7$  min,  
640 Dill et al. (2011)] places an inherent limit on the growth rate that can only be surpassed if the cell were to increase  
641 their polypeptide elongation rate, or if they could reduce the total protein and rRNA mass of the ribosome. The  
642 second point relates to the long-observed correlations between growth rate and cell size (Schaechter et al., 1958; Si  
643 et al., 2017), and between growth rate and ribosomal mass fraction. While both trends have sparked tremendous  
644 curiosity and driven substantial amounts of research in their own regards, these relationships are themselves  
645 intertwined. In particular, it is the need for cells to increase their absolute number of ribosomes under conditions  
646 of rapid growth that require cells to also grow in size. Further experiments are needed to test the validity of this  
647 hypothesis. In particular, we believe that the change in growth rate in response to translation-inhibitory drugs  
648 (such as chloramphenicol) could be quantitatively predicted, given one had precision measurement of the relevant  
649 parameters, including the fraction of actively translating ribosomes  $f_a$  and changes in the metabolic capacity of  
650 the cell (i.e. the rate that amino acids can be made available) for a particular growth condition.

651 While the generation of new ribosomes plays a dominant role in growth rate control, there exist other physical  
652 limits to the function of cellular processes. One of the key motivations for considering energy production was the  
653 physical constraints on total volume and surface area as cells vary their size (Harris and Theriot, 2018; Ojic et al.,  
654 2019). As *E. coli* get larger at faster growth rates, an additional constraint begins to arise in energy production and  
655 nutrient uptake due to the relative decrease in total surface area, where ATP is predominantly produced (Szenk  
656 et al., 2017). Specifically, the cell interior requires an amount of energy that scales cubically with cell size, but the  
657 available surface area only grows quadratically [*Figure 5(A)*]. While this threshold does not appear to be met for  
658 *E. coli* cells growing at  $2 \text{ hr}^{-1}$  or less, it highlights an additional constraint on growth given the apparent need to  
659 increase cell size in order to grow faster. This limit is relevant even to eukaryotic organisms, whose mitochondria  
660 exhibit convoluted membrane structures that nevertheless remain bacteria-sized organelles (Guo et al., 2018). In  
661 the context of bacterial growth and energy production more generally, we have mainly limited our analysis to  
662 the aerobic growth conditions associated with the proteomic data and further consideration will be needed for  
663 anaerobic growth.<sup>1</sup>

664 This work is by no means meant to be a complete dissection of bacterial growth rate control, and there are  
665 many aspects of the bacterial proteome and growth that we neglected to consider. For example, other recent work

666 (*Liebermeister et al., 2014; Hui et al., 2015; Schmidt et al., 2016*) has explored how the proteome is structured  
667 and how that structure depends on growth rate. In the work of *Hui et al. (2015)*, the authors coarse-grained the  
668 proteome into six discrete categories being related to either translation, catabolism, anabolism, and others related  
669 to signaling and core metabolism. The relative mass fraction of the proteome occupied by each sector could be  
670 modulated by external application of drugs or simply by changing the nutritional content of the medium. While we  
671 have explored how the quantities of individual complexes are related to cell growth, we acknowledge that higher-  
672 order interactions between groups of complexes or metabolic networks at a systems-level may reveal additional  
673 insights into how these growth-rate dependences are mechanistically achieved. Furthermore, while we anticipate  
674 the conclusions summarized here are applicable to a wide collection of bacteria with similar lifestyles as *E. coli*,  
675 other bacteria and archaea may have evolved other strategies that were not considered. Further experiments  
676 with the level of rigor now possible in *E. coli* will need to be performed in a variety of microbial organisms to learn  
677 more about how regulation of proteomic composition and growth rate control has evolved over the past 3.5 billion  
678 years.

## 679 Methods

### 680 Data Analysis and Availability

681 All proteomic measurements come from the experimental work of *Schmidt et al. (2016); Peebo et al. (2015); Val-*  
682 *gepea et al. (2013)* (mass spectrometry) and *Li et al. (2014)* (ribosomal profiling). Data curation and analysis was  
683 done programmatically in Python, and compiled data and analysis files are accessible through a [GitHub repository](#)  
684 (DOI:XXX) associated with this paper as well as on the associated [paper website](#). Additionally, we provide two in-  
685 teractive figures that allow for [rapid exploration of the compiled data sets](#) as well as [exploration of the parameter](#)  
686 [space of the minimal model](#).

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### 694 Competing Interests

695 The authors declare no competing interests.

# **Appendix for: Fundamental limits on the rate of bacterial cell division**

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<b>765</b>	<b>Estimation of <math>\langle \#ori \rangle / \langle \#ter \rangle</math> and <math>\langle \#ori \rangle</math>.</b>	<b>44</b>
<b>766</b>	<b>Derivation of Minimal Model for Nutrient-Mediated Growth Rate Control</b>	<b>45</b>

767 **Additional Estimates of Fundamental Biological Processes**

768 In the main text of this work, we present estimates for a significant number of fundamental biological processes  
769 that are necessary for cell division. While we believe the estimates provided in the main text provide a succinct  
770 summary of the corresponding process, we left out additional estimates of related processes for brevity. In this  
771 section of the appendix, we present these additional estimates in full.

772 **Nutrient Transport**

773 In the main text, we make passing mention that while transport carbon often comes in the form of carbohydrates  
774 and sugar alcohols while other critical elements – such as nitrogen, sulfur, and phosphorus – are transported as  
775 inorganic ions. Below, we present estimates for the transport requirements of these materials.

776 **Nitrogen**

777 We must first address which elemental sources must require active transport, meaning that the cell cannot acquire  
778 appreciable amounts simply via diffusion across the membrane. The permeability of the lipid membrane to a large  
779 number of solutes has been extensively characterized over the past century. Large, polar molecular species (such  
780 as various sugar molecules, sulfate, and phosphate) have low permeabilities while small, non-polar compounds  
781 (such as oxygen, carbon dioxide, and ammonia) can readily diffuse across the membrane. Ammonia, a primary  
782 source of nitrogen in typical laboratory conditions, has a permeability on par with water ( $\sim 10^5$  nm/s, BNID:110824).  
783 In nitrogen-poor conditions, *E. coli* expresses a transporter (AmtB) which appears to aid in nitrogen assimilation,  
784 though the mechanism and kinetic details of transport are still a matter of debate (*van Heeswijk et al., 2013*;  
785 *Khademi et al., 2004*). Beyond ammonia, another plentiful source of nitrogen come in the form of glutamate,  
786 which has its own complex metabolism and scavenging pathways. However, nitrogen is plentiful in the growth  
787 conditions examined in this work, permitting us to neglect nitrogen transport as a potential rate limiting process  
788 in cell division in typical experimental conditions.

789 **Phosphorus**

790 Phosphorus is critical to the cellular energy economy in the form of high-energy phosphodiester bonds making  
791 up DNA, RNA, and the NTP energy pool as well as playing a critical role in the post-translational modification of  
792 proteins and defining the polar-heads of lipids. In total, phosphorus makes up  $\approx 3\%$  of the cellular dry mass which  
793 in typical experimental conditions is in the form of inorganic phosphate. The cell membrane has remarkably low  
794 permeability to this highly-charged and critical molecule, therefore requiring the expression of active transport  
795 systems. In *E. coli*, the proton electrochemical gradient across the inner membrane is leveraged to transport inor-  
796 ganic phosphate into the cell (*Rosenberg et al., 1977*). Proton-solute symporters are widespread in *E. coli* (*Ramos*  
797 and *Kaback, 1977; Booth et al., 1979*) and can have rapid transport rates of 50 to 100 molecules per second for  
798 sugars and other solutes (BNID: 103159; 111777). As a more extreme example, the proton transporters in the F<sub>1</sub>-F<sub>0</sub>  
799 ATP synthase, which use the proton electrochemical gradient for rotational motion, can shuttle protons across the  
800 membrane at a rate of  $\approx 1000$  per second (BNID: 104890; 103390). In *E. coli* the PitA phosphate transport system  
801 has been shown to be very tightly coupled with the proton electrochemical gradient with a 1:1 proton:phosphate  
802 stoichiometric ratio (*Harris et al., 2001; Feist et al., 2007*). Taking the geometric mean of the aforementioned  
803 estimates gives a plausible rate of phosphate transport on the order of 300 per second. Illustrated in **Figure 2-**  
804 **Figure Supplement 1(A)**, we can estimate that  $\approx 200$  phosphate transporters are necessary to maintain an  $\approx 3\%$   
805 dry mass with a 5000 s division time. This estimate is consistent with observation when we examine the observed  
806 copy numbers of PitA in proteomic data sets (plot in **Figure 2-Figure Supplement 1(A)**). While our estimate is very  
807 much in line with the observed numbers, we emphasize that this is likely a slight overestimate of the number of  
808 transporters needed as there are other phosphorous scavenging systems, such as the ATP-dependent phosphate  
809 transporter Pst system which we have neglected.

810 **Sulfur**

811 Similar to phosphate, sulfate is highly-charged and not particularly membrane permeable, requiring active trans-  
812 port. While there exists a H<sup>+</sup>/sulfate symporter in *E. coli*, it is in relatively low abundance and is not well charac-  
813 terized (*Zhang et al., 2014a*). Sulfate is predominantly acquired via the ATP-dependent ABC transporter CysUWA

814 system which also plays an important role in selenium transport (*Sekowska et al., 2000; Sirko et al., 1995*). While  
815 specific kinetic details of this transport system are not readily available, generic ATP transport systems in prokary-  
816 otes transport on the order of 1 to 10 molecules per second (BNID: 109035). Combining this generic transport  
817 rate, measurement of sulfur comprising 1% of dry mass, and a 5000 second division time yields an estimate of  $\approx$   
818 1000 CysUWA complexes per cell (*Figure 2–Figure Supplement 1(B)*). Once again, this estimate is in notable agree-  
819 ment with proteomic data sets, suggesting that there are sufficient transporters present to acquire the necessary  
820 sulfur. In a similar spirit of our estimate of phosphorus transport, we emphasize that this is likely an overestimate  
821 of the number of necessary transporters as we have neglected other sulfur scavenging systems that are in lower  
822 abundance.

### 823 Additional Process of the Central Dogma

824 In the main text, we consider the processes underlying the backbone of the central dogma, namely DNA replication,  
825 RNA transcription, and protein translation. In this section we turn our attention to additional processes related  
826 to the central dogma, primarily dNTP synthesis for DNA replication and amino-acyl tRNA synthesis for translation.  
827 Additionally, we explore in more detail the estimates shown in *Figure 7(A)* for the RNA polymerase requirements  
828 of mRNA and tRNA synthesis.

#### 829 dNTP synthesis

830 The four major dNTPs (dATP, dTTP, dCTP, and dGTP) serve as the fundamental units of the genetic code. Thus, to  
831 faithfully replicate the chromosome, the cell must be able to synthesize enough of these bases in the first place.  
832 All dNTPs are synthesized *de novo* in separate pathways, requiring different building blocks. However, a critical  
833 step present in all dNTP synthesis pathways is the conversion from ribonucleotide to deoxyribonucleotide via the  
834 removal of the 3' hydroxyl group of the ribose ring (*Rudd et al., 2016*). This reaction is mediated by a class of  
835 enzymes termed ribonucleotide reductases, of which *E. coli* possesses two aerobically active complexes (termed  
836 I and II) and a single anaerobically active enzyme. Due to their peculiar formation of a radical intermediate, these  
837 enzymes have received much biochemical, kinetic, and structural characterization. One such work (*Ge et al.,*  
838 *2003*) performed a detailed *in vitro* measurement of the steady-state kinetic rates of these complexes, revealing a  
839 turnover rate of  $\approx$  10 dNTP per second.

840 Since this reaction is central to the synthesis of all dNTPs, it is reasonable to consider the abundance of these  
841 complexes is a measure of the total dNTP production in *E. coli*. Illustrated schematically in *Figure 6(A)*, we consider  
842 the fact that to replicate the cell's genome, on the order of  $\approx$  10<sup>7</sup> dNTPs must be synthesized. Assuming a pro-  
843 duction rate of 10 per second per ribonucleotide reductase complex and a cell division time of 5000 seconds, we  
844 arrive at an estimate of  $\approx$  200 complexes needed per cell. As shown in the bottom panel of *Figure Supplement 1*  
845 (A), this estimate agrees with the experimental measurements of these complexes abundances within  $\approx$  1/2 an  
846 order of magnitude. Extension of this estimate across a continuum of growth rate, including the fact that multiple  
847 chromosomes can be replicated at a given time, is shown as a grey transparent line in *Figure Supplement 1*. Sim-  
848 ilarly to our point estimate, this refinement agrees well with the data, accurately describing both the magnitude  
849 of the complex abundance and the dependence on growth rate.

850 Recent work has revealed that during replication, the ribonucleotide reductase complexes coalesce to form  
851 discrete foci colocalized with the DNA replisome complex (*Sánchez-Romero et al., 2011*). This is particularly pro-  
852 nounced in conditions where growth is slow, indicating that spatial organization and regulation of the activity of  
853 the complexes plays an important role.

#### 854 mRNA and tRNA Synthesis

855 In *Figure 7* of the main text, we present with limited explanation estimates for the number of RNA polymerases  
856 needed to synthesize enough mRNA and tRNA molecules. Here, we present a rationalization for these estimates.

857 To form a functional protein, all protein coding genes must first be transcribed from DNA to form an mRNA  
858 molecule. While each protein requires an mRNA blueprint, many copies of the protein can be synthesized from  
859 a single mRNA. Factors such as strength of the ribosomal binding site, mRNA stability, and rare codon usage  
860 frequency dictate the number of proteins that can be made from a single mRNA, with yields ranging from 10<sup>1</sup>  
861 to 10<sup>4</sup> (BNID: 104186; 100196; 106254). Computing the geometric mean of this range yields  $\approx$  1000 proteins

862 synthesized per mRNA, a value that agrees with experimental measurements of the number of proteins per cell  
863 ( $\approx 3 \times 10^6$ , BNID: 100088) and total number of mRNA per cell ( $\approx 3 \times 10^3$ , BNID: 100064).

864 This estimation captures the *steady-state* mRNA copy number, meaning that at any given time, there will exist  
865 approximately 3000 unique mRNA molecules. To determine the *total* number of mRNA that need to be synthesized  
866 over the cell's lifetime, we must consider degradation of the mRNA. In most bacteria, mRNAs are rather unstable  
867 with life times on the order of several minutes (BNID: 104324; 106253; 111927; 111998). For convenience, we  
868 assume that the typical mRNA in our cell of interest has a typical lifetime of  $\approx 300$  seconds. Using this value, we  
869 can determine the total mRNA production rate to maintain a steady-state copy number of 3000 mRNA per cell.  
870 While we direct the reader to the appendix for a more detailed discussion of mRNA transcriptional dynamics, we  
871 state here that the total mRNA production rate must be on the order of  $\approx 15$  mRNA per second. In *E. coli*, the  
872 average protein is  $\approx 300$  amino acids in length (BNID: 108986), meaning that the corresponding mRNA is  $\approx 900$   
873 nucleotides which we will further approximate as  $\approx 1000$  nucleotides to account for the non-protein coding regions  
874 on the 5' and 3' ends. This means that the cell must have enough RNA polymerase molecules about to sustain a  
875 transcription rate of  $\approx 1.5 \times 10^4$  nucleotides per second. Knowing that a single RNA polymerase polymerizes RNA  
876 at a clip of 40 nucleotides per second, we arrive at a comfortable estimate of  $\approx 250$  RNA polymerase complexes  
877 needed to satisfy the mRNA demands of the cell. It is worth noting that this number is approximately half of that  
878 required to synthesize enough rRNA, as we saw in the previous section. We find this to be a striking result as these  
879 250 RNA polymerase molecules are responsible for the transcription of the  $\approx 4000$  protein coding genes that are  
880 not ribosome associated.

881 We now turn our attention to the synthesis of tRNA. Unlike mRNA or rRNA, each individual tRNA is remarkably  
882 short, ranging from 70 to 95 nucleotides each (BNID: 109645; 102340). What they lack in length, they make up  
883 for in abundance, with reported values ranging from  $\approx 5 \times 10^4$  (BNID: 105280) to  $\approx 5 \times 10^5$  (BNID: 108611). To test  
884 tRNA synthesis as a possible growth-rate limiting stage, we will err towards a higher abundance of  $\approx 5 \times 10^5$  per cell.  
885 Combining the abundance and tRNA length measurements, we make the estimate that  $\approx 5 \times 10^7$  nucleotides are  
886 sequestered in tRNA per cell. Unlike mRNA, tRNA is remarkably stable with typical lifetimes *in vivo* on the order of  $\approx$   
887 48 hours (Abelson et al., 1974; Svenningsen et al., 2017) – well beyond the timescale of division. Once again using  
888 our rule-of-thumb for the rate of transcription to be 40 nucleotides per second and assuming a division time of  $\approx$   
889 5000 seconds, we arrive at an estimate of  $\approx 200$  RNA polymerases to synthesize enough tRNA. This requirement  
890 pales in comparison to the number of polymerases needed to generate the rRNA and mRNA pools and can be  
891 neglected as a significant transcriptional burden.

## 892 tRNA Charging

893 In the previous subsection, we focused solely on estimating the number of RNA polymerases needed for the  
894 generation of the tRNA molecule itself. We now explore the protein complex requirements for ligation of the  
895 appropriate amino acid to each tRNA. We begin by again using an estimate of  $\approx 3 \times 10^6$  proteins per cell at a 5000  
896 s division time (BNID: 115702) and a typical protein length of  $\approx 300$  amino acids (BNID: 100017), we can estimate  
897 that a total of  $\approx 10^9$  amino acids are stitched together by peptide bonds.

898 How many tRNAs are needed to facilitate this remarkable number of amino acid delivery events to the trans-  
899 lating ribosomes? It is important to note that tRNAs are recycled after they've passed through the ribosome and  
900 can be recharged with a new amino acid, ready for another round of peptide bond formation. While some *in vitro*  
901 data exists on the turnover of tRNA in *E. coli* for different amino acids, we can make a reasonable estimate by  
902 comparing the number of amino acids to be polymerized to cell division time. Using our stopwatch of 5000 s and  
903  $10^9$  amino acids, we arrive at a requirement of  $\approx 2 \times 10^5$  tRNA molecules to be consumed by the ribosome per  
904 second.

905 There are many processes which go into synthesizing a tRNA and ligating it with the appropriate amino acids.  
906 As we discussed previously, there appear to be more than enough RNA polymerases per cell to synthesize the  
907 needed pool of tRNAs. Without considering the many ways in which amino acids can be scavenged or synthesized  
908 *de novo*, we can explore ligation the as a potential rate limiting step. The enzymes which link the correct amino  
909 acid to the tRNA, known as tRNA synthetases or tRNA ligases, are incredible in their proofreading of substrates  
910 with the incorrect amino acid being ligated once out of every  $10^4$  to  $10^5$  events (BNID: 103469). This is due in part  
911 to the consumption of energy as well as a multi-step pathway to ligation. While the rate at which tRNA is ligated is

**Table 1.** Overview of proteomic data sets.

Author	Method	Reported Quantity
Taniguchi <i>et al.</i> (2010)	YFP-fusion, cell fluorescence	fg/copies per cell
Valgepea <i>et al.</i> (2012)	mass spectrometry	fg/copies per cell
Peebo <i>et al.</i> (2014)	mass spectrometry	fg/copies per fl
Li <i>et al.</i> (2014)	ribosomal profiling	fg/copies per cell <sup>a</sup>
Soufi <i>et al.</i> (2015)	mass spectrometry	fg/copies per cell
Schmidt <i>et al.</i> (2016)	mass spectrometry	fg/copies per cell <sup>b</sup>

a. The reported values assume that the proteins are long-lived compared to the generation time but are unable to account for post-translational modifications that may alter absolute protein abundances.

b. This mass spectrometry approach differs substantially from the others since in addition to the relative proteome-wide abundance measurements, the authors performed absolute quantification of 41 proteins across all growth conditions (see section on Additional Considerations of Schmidt *et al.* Data Set for more details on this).

912 highly dependent on the identity of the amino acid, it is reasonable to state that the typical tRNA synthetase has  
913 charging rate of  $\approx 20$  AA per tRNA synthetase per second (BNID: 105279).

914 We can make an assumption that amino-acyl tRNAs are in steady-state where they are produced at the same  
915 rate they are consumed, meaning that  $2 \times 10^5$  tRNAs must be charged per second. Combining these estimates  
916 together, as shown schematically in **Figure 8–Figure Supplement 1**, yields an estimate of  $\sim 10^4$  tRNA synthetases  
917 per cell with a division time of 5000 s. This point estimate is in very close agreement with the observed number of  
918 synthetases (the sum of all 20 tRNA synthetases in *E. coli*). This estimation strategy seems to adequately describe  
919 the observed growth rate dependence of the tRNA synthetase copy number (shown as the grey line in **Figure 8–**  
920 **Figure Supplement 1**, suggesting that the copy number scales with the cell volume.

921 In total, the estimated and observed  $\sim 10^4$  tRNA synthetases occupy only a meager fraction of the total cell  
922 proteome, around 0.5% by abundance. It is reasonable to assume that if tRNA charging was a rate limiting pro-  
923 cess, cells would be able to increase their growth rate by devoting more cellular resources to making more tRNA  
924 synthetases. As the synthesis of tRNAs and the corresponding charging can be highly parallelized, we can argue that  
925 tRNA charging is not a rate limiting step in cell division, at least for the growth conditions explored in this work.

## 926 Experimental Details Behind Proteomic Data

927 Here we provide a brief summary of the experiments behind each proteomic data set considered. The purpose  
928 of this section is to identify how the authors arrived at absolute protein abundances. In the following section (see  
929 section on Summary of Proteomic Data) we will then provide a summary of the protein abundance measurements.  
930 Table 1 provides an overview of the publications we considered. These are predominately mass spectrometry-  
931 based, with the exception of the work from Li *et al.* (2014) which used ribosomal profiling, and the fluorescence-  
932 based counting done in Taniguchi *et al.* (2010). After having compiled and comparing these measurements, we  
933 noted substantial deviations in the measurements from Taniguchi *et al.* (2010) and Soufi *et al.* (2015) (shown in  
934 the following section), and decided to only use the data from Taniguchi *et al.* (2010); Li *et al.* (2014); Valgepea  
935 *et al.* (2013); Peebo *et al.* (2015) in the main text. For completeness, we include these additional datasets in our  
936 discussion of the experimental data.

## 937 Fluorescence based measurements

938 In the work of Taniguchi *et al.* (2010), the authors used a chromosomal YFP fusion library where individual strains  
939 have a specific gene tagged with a YFP-coding sequence. 1018 of their 1400 attempted strains were used in the  
940 work. A fluorescence microscope was used to collect cellular YFP intensities across all these strains. Through au-  
941 tomated image analysis, the authors normalized intensity measurements by cell size to account for the change  
942 in size and expression variability across the cell cycle. Following correction of YFP intensities for cellular autoflu-  
943 orescence, final absolute protein levels were determined by a calibration curve with single-molecule fluorescence  
944 intensities. This calibration experiment was performed separately using a purified YFP solution.

945 **Ribosomal profiling measurements**

946 The work of *Li et al. (2014)* takes a sequencing based approach to estimate protein abundance. Ribosomal pro-  
947 filing, which refers to the deep sequencing of ribosome-protected mRNA fragments, can provide a quantitative  
948 measurement of the protein synthesis rate. As long as the protein life-time is long relative to the cell doubling  
949 time, it is possible to estimate absolute protein copy numbers. The absolute protein synthesis rate has units of  
950 proteins per generation, and for stable proteins will also correspond to the protein copy number per cell.

951 In the experiments, ribosome-protected mRNA is extracted from cell lysate and selected on a denaturing poly-  
952 acrylamide gel for deep sequencing (15–45 nt long fragments collected and sequenced by using an Illumina HiSeq  
953 2000 in *Li et al. (2014)*). Counts of ribosome footprints from the sequencing data were then corrected empiri-  
954 cally for position-dependent biases in ribosomal density across each gene, as well as dependencies on specific  
955 sequences including the Shine-Dalgarno sequence. These data-corrected ribosome densities represent relative  
956 protein synthesis rates. Absolute protein synthesis rates are obtained by multiplying the relative rates by the total  
957 cellular protein per cell. The total protein per unit volume was determined with the Lowry method to quantify  
958 total protein, calibrated against bovine serum albumin (BSA). By counting colony-forming units following serial  
959 dilution of their cell cultures, they then calculated the total protein per cell.

960 **Mass spectrometry measurements**

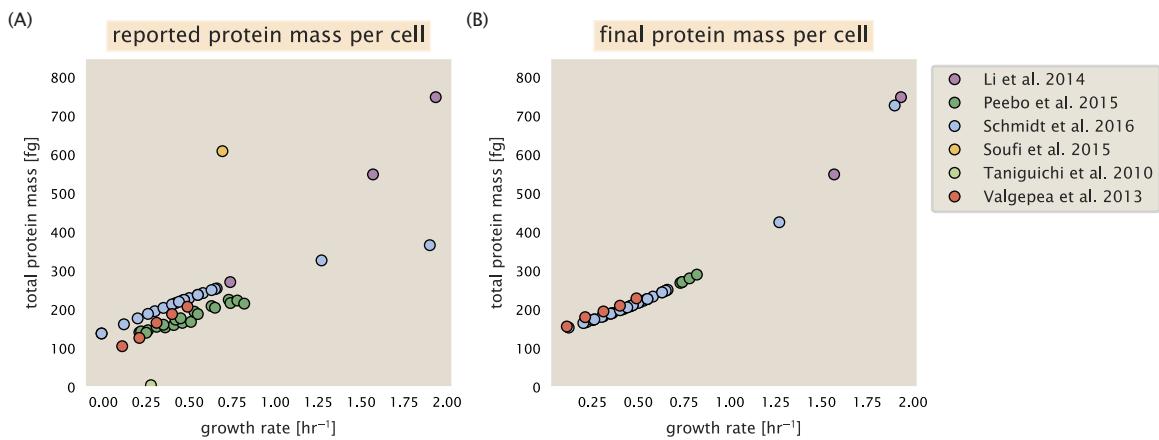
961 Perhaps not surprisingly, the data is predominantly mass spectrometry based. This is largely due to tremendous  
962 improvements in the sensitivity of mass spectrometers, as well as improvements in sample preparation and data  
963 analysis pipelines. It is now a relatively routine task to extract protein from a cell and quantify the majority of  
964 proteins present by shotgun proteomics. In general, this involves lysing cells, enzymatically digesting the proteins  
965 into short peptide fragments, and then introducing them into the mass spectrometer (e.g. with liquid chromatog-  
966 raphy and electrospray ionization), which itself can have multiple rounds of detection and further fragmentation  
967 of the peptides.

968 Most quantitative experiments rely on labeling protein with stable isotopes, which allow multiple samples  
969 to be measured together by the mass spectrometer. By measuring samples of known total protein abundance  
970 simultaneously (i.e. one sample of interest, and one reference), it is possible to determine relative protein abun-  
971 dances. Absolute protein abundances can be estimated following the same approach used above for ribosomal  
972 profiling, which is to multiply each relative abundance measurement by the total cellular protein per cell. This  
973 is the approach taken by *Valgepea et al. (2013)*; *Peebo et al. (2015)* and *Soufi et al. (2015)*, with relative protein  
974 abundances determined based on the relative peptide intensities (label free quantification 'LFQ' intensities). For  
975 the data of *Valgepea et al. (2013)*, total protein per cell was determined by measuring total protein by the Lowry  
976 method, and counting colony-forming units following serial dilution. For the data from *Peebo et al. (2015)*, the  
977 authors did not determine cell quantities and instead report the cellular protein abundances in protein per unit  
978 volume by assuming a mass density of 1.1 g/ml, with a 30% dry mass fraction.

979 An alternative way to arrive at absolute protein abundances is to dope in synthetic peptide fragments of known  
980 abundance. These can serve as a direct way to calibrate mass spectrometry signal intensities to absolute mass.  
981 This is the approach taken by *Schmidt et al. (2016)*. In addition to a set of shotgun proteomic measurements to  
982 determine proteome-wide relative abundances, the authors also performed absolute quantification of 41 proteins  
983 covering over four orders of magnitude in cellular abundance. Here, a synthetic peptide was generated for each of  
984 the proteins, doped into each protein sample, and used these to determine absolute protein abundances of the 41  
985 proteins. These absolute measurements, determined for every growth condition, were then used as a calibration  
986 curve to convert proteomic-wide relative abundances into absolute protein abundance per cell. A more extensive  
987 discussion of the *Schmidt et al. (2016)* data set can be found in Section Additional Considerations of Schmidt et al.  
988 Data Set.

989 **Summary of Proteomic Data**

990 In the work of the main text we only used the data from *Valgepea et al. (2013)*; *Li et al. (2014)*; *Peebo et al. (2015)*;  
991 *Schmidt et al. (2016)*. As shown in *Figure 12(A)*, the reported total protein abundances in the work of *Taniguchi*  
992 *et al. (2010)* and *Soufi et al. (2015)* differed quite substantially from the other work. For the work of *Taniguchi*



**Figure 12. Summary of the growth-rate dependent total protein abundance for each data set.** (A) Total protein abundance per cell as originally reported in the data sets of *Taniguchi et al. (2010)*; *Valgepea et al. (2013)*; *Li et al. (2014)*; *Soufi et al. (2015)*; *Peebo et al. (2015)*; *Schmidt et al. (2016)*. Note that the data from *Peebo et al. (2015)* only reported protein abundances per unit volume and total protein per cell was found by multiplying these by the growth-rate dependent cell size as determined by *Si et al. (2017)*. (B) Adjusted total protein abundances across the proteomic data sets are summarized. Protein abundances were adjusted so that all data shared a common set of growth-rate dependent total protein per cell and cellular protein concentration following the cell size expectations of *Si et al. (2017)* (see section on Estimation of Cell Size and Surface Area for further details).

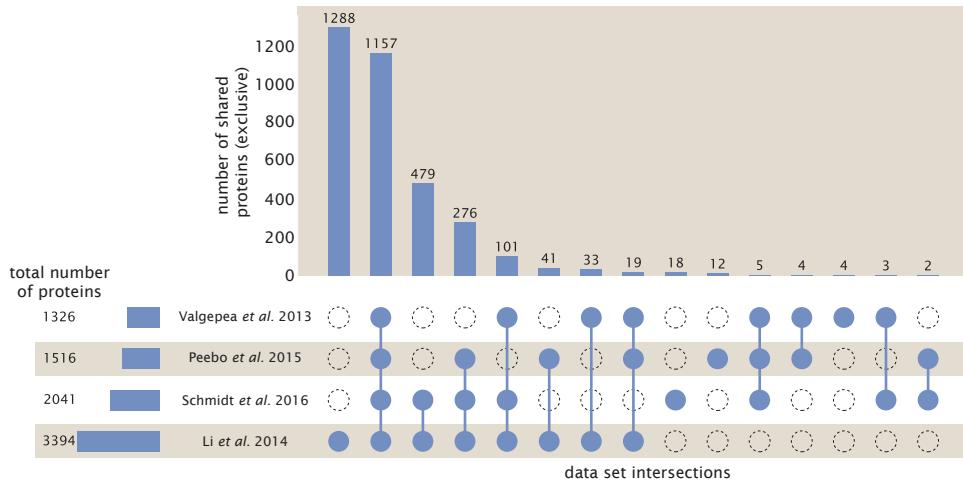
993 *et al. (2010)* this is in part due to a lower coverage in total proteomic mass quantified, though we also noticed that  
 994 most proteins appear undercounted when compared to the other data.

995 *Figure 12(B)* summarizes the total protein mass for each data set used in our final compiled data set. Our  
 996 inclination initially was to leave reported copy numbers untouched, but a notable discrepancy between the scaling  
 997 of the total protein per cell between *Schmidt et al. (2016)* and the other data sets forced us to dig deeper into  
 998 those measurements (compare *Schmidt et al. (2016)* and *Li et al. (2014)* data in *Figure 12(A)*). The particular trend  
 999 in *Schmidt et al. (2016)* appears to be due to assumptions made about cell size and we provide a more extensive  
 1000 discussion and analysis of their data in Additional Considerations of Schmidt et al. Data Set. As a compromise, and  
 1001 in an effort to treat all data equally, we instead applied a correction factor to all protein abundance values based  
 1002 on a data-driven estimate of total protein per cell. Here we used cell size measurements from *Si et al. (2017, 2019)*,  
 1003 and an estimate of total protein content through expected dry mass. Total protein per cell was then determined  
 1004 using available data on total DNA, RNA, and protein from *Basan et al. (2015)*; *Dai et al. (2016)*, which account for  
 1005 the majority of dry mass in the cell. We describe these details further in sections on Estimation of Cell Size and  
 1006 Surface Area and Estimation of Total Protein Content per Cell that follows.

1007 Lastly, in *Figure 13* we show the total proteomic coverage and overlap of proteins quantified across each data  
 1008 set. Here we have used an UpSet diagram (*Lex et al., 2014*) to compare the data. Overall, the overlap in quantified  
 1009 proteins is quite high, with 1157 proteins quantified across all data sets. The sequencing based approach of *Li*  
 1010 *et al. (2014)* has substantially higher coverage compared to the mass spectrometry data sets (3394 genes versus  
 1011 the 2041 genes quantified in the work of *Schmidt et al. (2016)*). However, in terms of total protein mass, the data  
 1012 from *Li et al. (2014)*; *Schmidt et al. (2016)*; *Peebo et al. (2015)* each quantify roughly equivalent total protein mass.  
 1013 An exception to this is in the data from *Valgepea et al. (2013)*, where we find that the total protein quantified in  
 1014 *Valgepea et al. (2013)* is 90-95 % of the total protein mass (when using the data from *Schmidt et al. (2016)* as a  
 1015 reference).

#### 1016 **Estimation of Cell Size and Surface Area**

1017 Since most of the proteomic data sets lack cell size measurements, we chose instead to use a common estimate  
 1018 of size for any analysis requiring cell size or surface area. Since each of the data sets used either K-12 MG1655 or  
 1019 its derivative, BW25113 (from the lab of Barry L. Wanner; the parent strain of the Keio collection (*Datsenko and*  
 1020 *Wanner, 2000; Baba et al., 2006*)), below we fit the MG1655 cell size data from the supplemental material of *Si*



**Figure 13. Comparison of proteomic coverage across different data sets.** An UpSet diagram (*Lex et al., 2014*) summarizes the total number of protein coding genes whose protein abundance was reported in the data sets of *Valgepea et al. (2013)*; *Li et al. (2014)*; *Schmidt et al. (2016)*; *Peebo et al. (2015)*. Bar plot on bottom left indicates the total number of genes reported in each individual data. The main bar plot summarizes the number of unique proteins identified across overlapping subsets of the data. For example, in the first column only the data from *Li et al. (2014)* is considered (indicated by solid blue circle) and 1288 proteins are identified as exclusive to the data set. In the second column, the intersection of all four data sets is considered, with 1157 proteins quantified across them. This follows for each additional column in the plot, with the subset under consideration denoted by the solid blue circles.

et al. (2017, 2019) using the `optimize.curve_fit` function from the Scipy python package (*Virtanen et al., 2020*). A quick comment on nomenclature: throughout the text, we usually refer to cell size, in units of  $\mu\text{m}^3$ ; however, on occasion we will mention size as a volume in units of fL.

The average size measurements from each of their experiments are shown in **Figure 14**, with cell length and width shown in (A) and (B), respectively. The length data was well described by the exponential function  $0.5 e^{1.09 \cdot \lambda} + 1.76 \mu\text{m}$ , while the width data was well described by  $0.64 e^{0.24 \cdot \lambda} \mu\text{m}$ . In order to estimate cell size we take the cell as a cylinder with two hemispherical ends (*Si et al., 2017*; *Basan et al., 2015*). Specifically, cell size is estimated from,

$$V = \pi \cdot r^2 \cdot (l - 2r/3), \quad (5)$$

where  $r$  is half the cell width. A best fit to the data is described by  $0.533 e^{1.037 \cdot \lambda} \mu\text{m}^3$ . Calculation of the cell surface area is given by,

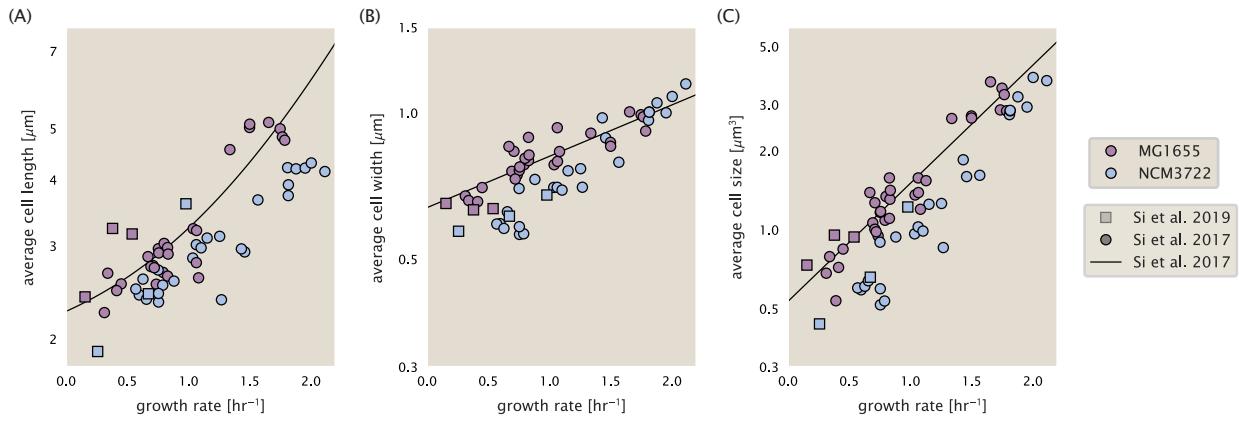
$$S = \eta \cdot \pi \left( \frac{\eta \cdot \pi}{4} - \frac{\pi}{12} \right)^{-2/3} V^{2/3}, \quad (6)$$

where  $\eta$  is the aspect ratio ( $\eta = l/w$ ) (*Ojkic et al., 2019*).

### 1031 Estimation of Total Protein Content per Cell

In order to estimate total protein per cell for a particular growth rate, we begin by estimating the cell size from the fit shown in **Figure 14(C)** (cell size =  $0.533 e^{1.037 \cdot \lambda} \mu\text{m}^3$ , as noted in the previous section). We then estimate the total protein content from the total dry mass of the cell. Here we begin by noting that for almost the entire range of growth rates considered here, protein, DNA, and RNA were reported to account for at least 90 % of the dry mass (*Basan et al. (2015)*). The authors also found that the total dry mass concentration was roughly constant across growth conditions. Under such a scenario, we can calculate the total dry mass concentration for protein, DNA, and RNA, which is given by  $1.1 \text{ g/ml} \times 30 \% \times 90 \% \text{ or about } [M_p] = 300 \text{ fg per fL}$ . Multiplying this by our prediction of cell size gives the total dry mass per cell.

However, even if dry mass concentration is relatively constant across growth conditions, it is not obvious how protein concentration might vary due to the substantial increase in rRNA at faster growth rates (*Dai et al. (2016)*). The increase in rRNA increases from the linear increase in ribosomal content with faster growth rate (*Scott et al.*



**Figure 14. Summary of size measurements from Si et al. 2017, 2019.** Cell lengths and widths were measured from cell contours obtained from phase contrast images, and refer to the long and short axis respectively. (A) Cell lengths and (B) cell widths show the mean measurements reported (they report 140-300 images and 5,000-30,000 for each set of samples; which likely means about 1,000-5,000 measurements per mean value reported here since they considered about 6 conditions at a time). Fits were made to the MG1655 strain data; length:  $0.5 e^{1.09 \cdot \lambda} + 1.76 \mu\text{m}$ , width:  $0.64 e^{0.24 \cdot \lambda} \mu\text{m}$ . (C) Cell size was calculated as cylinders with two hemispherical ends (Equation 5). The MG1655 strain data gave a best fit of  $0.533 e^{1.037 \cdot \lambda} \mu\text{m}^3$ .

1043 (2010)), since it makes up about about 2/3 or the ribosomal mass. To proceed we therefore relied on experimental  
 1044 measurements of total DNA content per cell from *Basan et al. (2015)*, and RNA to protein ratios that were mea-  
 1045 sured in *Dai et al.* (and cover the entire range of growth conditions considered here). These are reproduced in  
 1046 *Figure 15(A)* and (B), respectively.

1047 Assuming that the protein, DNA, and RNA account for 90 % of the total dry mass, the protein mass can then de-  
 1048 termined by first subtracting the experimentally measured DNA mass, and then using the experimental estimate  
 1049 of the RNA to protein ratio. The total protein per cell is will be related to the summed RNA and protein mass by,

$$M_P = \frac{[M_P + M_{RNA}]}{1 + (RP_{ratio})}. \quad (7)$$

1050 ( $RP_{ratio}$  refers to the RNA to protein ratio as measured by *Dai et al.*). In *Figure 15(C)* we plot the estimated cellular  
 1051 concentrations for protein, DNA, and RNA from these calculations, and in *Figure 15(D)* we plot their total expected  
 1052 mass per cell. This later quantity is the growth rate-dependent total protein mass that was used to estimate total  
 1053 protein abundance across all data sets (and summarized in *Figure 12(B)*).

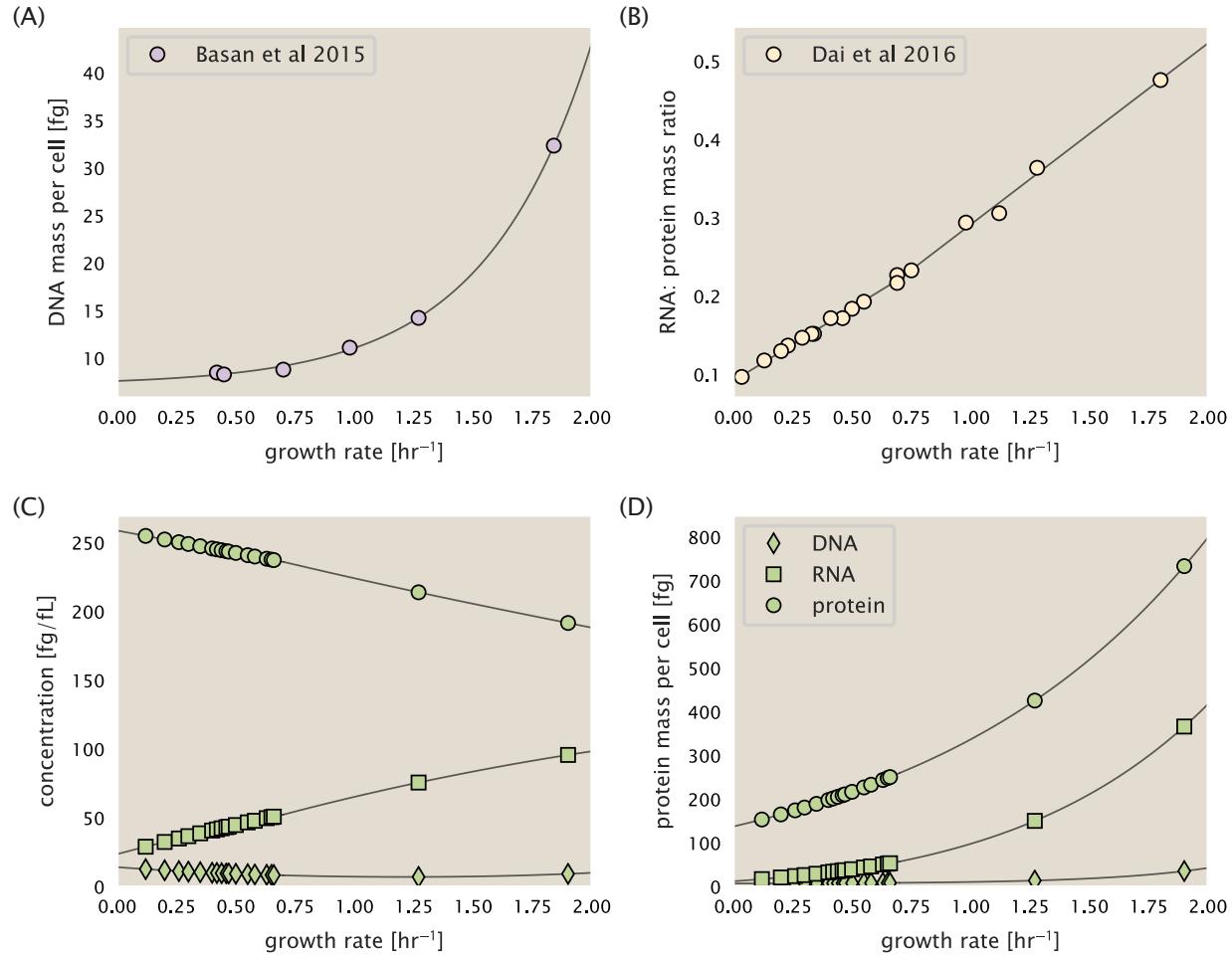
### 1054 Estimating Volume and Number of Amino Acids from Ribosome Copy Number

1055 Towards the end of the main text, we examine a coarse-grained model of nutrient-limited growth. A key point  
 1056 in our analysis was to consider how elongation rate  $r_e$  and growth rate  $\lambda$  vary with respect to the experimentally  
 1057 observed changes in cell size, total number of peptide bonds per cell  $N_{pep}$ , and ribosomal content. In order to  
 1058 restrict parameters to those observed experimentally, but otherwise allow us to explore the model, we performed  
 1059 a phenomenological fit of  $N_{pep}$  and  $V$  as a function of the measured ribosomal copy number  $R$ . As has been  
 1060 described in the preceding sections of this supplement, we estimate cell volume for each growth condition using  
 1061 the size measurements from *Si et al. (2017, 2019)*, and  $N_{pep}$  is approximated by taking the total protein mass and  
 1062 dividing this number by the average mass of an amino acid, 110 Da (BNID: 104877).

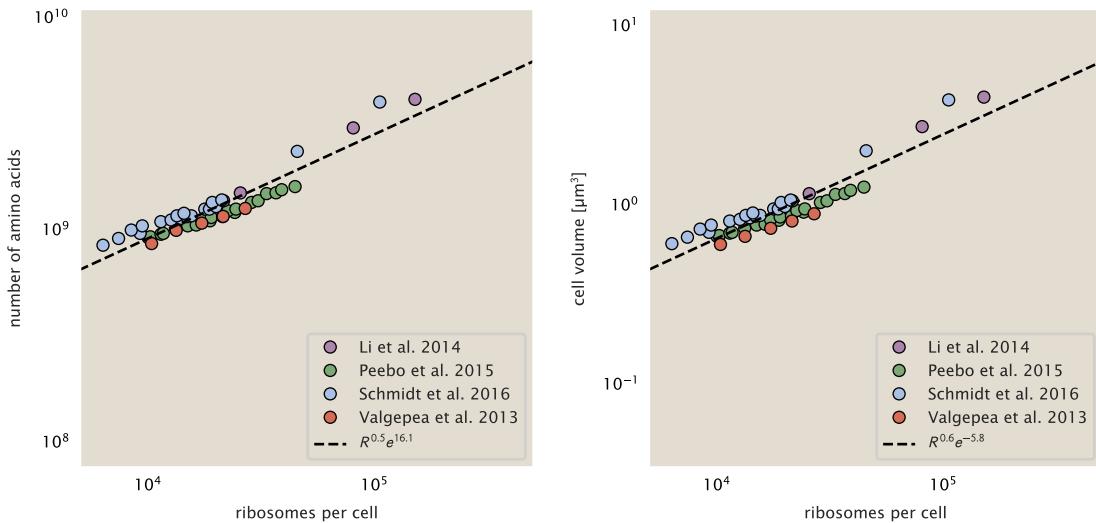
1063 Given the exponential scaling of  $V$  and  $N_{pep}$  with growth rate, we performed a linear regression of the log trans-  
 1064 form of these parameters as a function of the log transform of the ribosome copy number. Using optimization  
 1065 by minimization, we estimated the best-fit values of the intercept and slope for each regression. *Figure 16* shows  
 1066 the result of each regression as a dashed line.

### 1067 Additional Considerations of Schmidt et al. Data Set

1068 While the data set from *Schmidt et al. (2016)* remains a heroic effort that our labs continue to return to as a  
 1069 resource, there were steps taken in their calculation of protein copy number that we felt needed further consider-



**Figure 15. Empirical estimate of cellular protein, DNA, and RNA as a function of growth rate.** (A) Measured DNA mass per cell as a function of growth rate, reproduced from Basan *et al.* 2015. The data was fit to an exponential curve (DNA mass in fg per cell is given by  $0.42 e^{2.23 \cdot \lambda} + 7.2$  fg per cell, where  $\lambda$  is the growth rate in  $\text{hr}^{-1}$ ). (B) RNA to protein measurements as a function of growth rate. The data was fit to two lines (shown in black) due to the change in slope at slower growth rates Neidhardt *et al.* (1991); Dai *et al.* (2016). For growth rates below  $0.7 \text{ hr}^{-1}$ , the RNA/protein ratio is  $0.18 \cdot \lambda + 0.093$ , while for growth rates faster than  $0.7 \text{ hr}^{-1}$  the RNA/protein ratio is given by  $0.25 \cdot \lambda + 0.035$ . For (A) and (B) cells are grown under varying levels of nutrient limitation, with cells grown in minimal media with different carbon sources for the slowest growth conditions, and rich-defined media for fast growth rates. (C) Estimation of cellular protein, DNA, and RNA concentration. (D) Total cellular mass estimated for protein, DNA, and RNA using the cell size calculated in Estimation of Cell Size and Surface Area. Symbols (diamond: DNA, square: RNA, circle: protein) show estimated values of mass concentration and mass per cell for the specific growth rates in Schmidt *et al.* (2016).

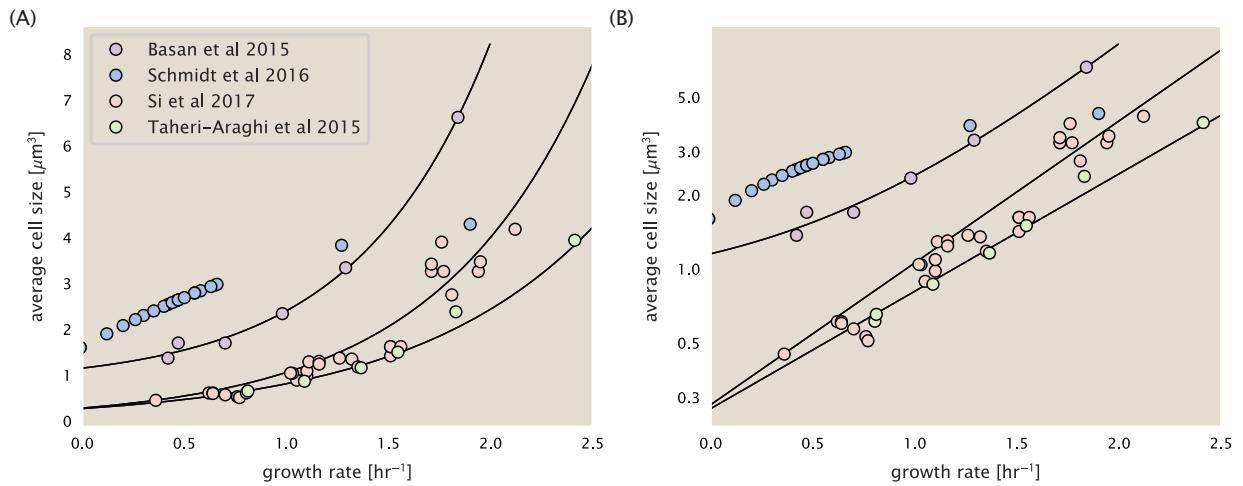


**Figure 16. Phenomenological regression of cell volume and number of amino acids per cell as a function of the ribosome copy number.** Colored points correspond to the measured value (or calculated value in the case of the cell volume) with colors denoting different data sets. The dashed black line shows the result of the fit, with the functional form of the equation given in the legend with  $R$  representing the ribosome copy number.

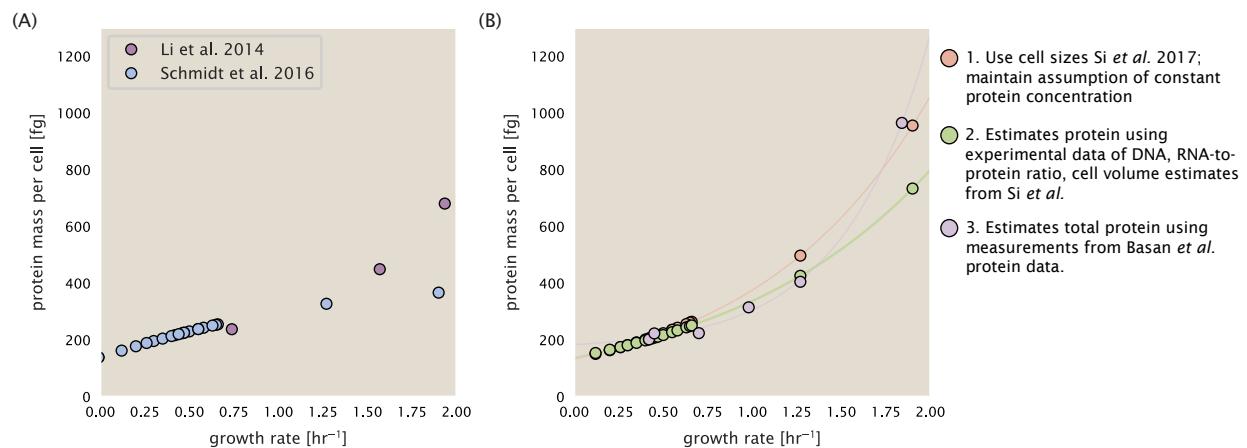
ation. In particular, the authors made an assumption of constant cellular protein concentration across all growth conditions and used measurements of cell volume that appear inconsistent with an expected exponential scaling of cell size with growth rate that is well-documented in *E. coli* (*Schaechter et al. (1958); Taheri-Araghi et al. (2015); Si et al. (2017)*).

We begin by looking at their cell volume measurements, which are shown in blue in Figure *Figure 17*. As a comparison, we also plot cell sizes reported in three other recent papers: measurements from Taheri-Araghi et al. and Si et al. come from the lab of Suckjoon Jun, while those from Basan et al. come from the lab of Terence Hwa. Each set of measurements used microscopy and cell segmentation to determine the length and width, and then calculated cell size by treating the cell as a cylinder with two hemispherical ends, as we considered in the previous section. While there is notable discrepancy between the two research groups, which are both using strain NCM3722, Basan et al. found that this came specifically from uncertainty in determining the cell width. This is prone to inaccuracy given the small cell size and optical resolution limits (further described in their supplemental text). Perhaps the more concerning point is that while each of these alternative measurements show an exponential increase in cell size at faster growth rates, the measurements used by Schmidt et al. appear to plateau. This resulted in an analogous trend in their final reported total cellular protein per cell as shown in *Figure 18* (purple data points), and is in disagreement with other measurements of total protein at these growth rates (*Basan et al., 2015*).

Since it is not obvious how measurements of cell size influenced their reported protein abundances, in the following subsections we begin by considering how the authors determined total protein mass per cell. We then consider three different approaches to estimate the growth-rate dependent total protein mass and compare these estimates with those reported by Schmidt et al. (2016). Those results are summarized in *Figure 17(B)*, with the original values from both Schmidt et al. (2016) and Li et al. (2014) shown in *Figure 17(A)* for reference. For most growth conditions, we find reasonable agreement between our estimates and the reported total protein per cell. However, for the fastest growth conditions, with glycerol + supplemented amino acids, and LB media, all estimates are substantially higher than those originally reported. This is the main reason why we chose to readjust protein abundance as shown in *Figure 12(B)* (with the calculation described in section Estimation of Total Protein Content per Cell).



**Figure 17. Measurements of cell size as a function of growth rate.** (A) Plot of the reported cell sizes from several recent papers. The data in blue come from Volkmer and Heinemann, 2011 ([Volkmer and Heinemann \(2011\)](#)) and were used in the work of Schmidt *et al.*. Data from the lab of Terence Hwa are shown in purple ([Basan \*et al.\* \(2015\)](#)), while the two data sets shown in green and light red come from the lab of Suckjoon Jun ([Taheri-Araghi \*et al.\* \(2015\); Si \*et al.\* \(2017\)](#)). (B) Same as in (A) but with the data plotted on a logarithmic y-axis to highlight the exponential scaling that is expected for *E. coli*.



**Figure 18. Alternative estimates of total cellular protein for the growth conditions considered in Schmidt et al.** (A) The original protein mass from Schmidt *et al.* and Li *et al.* are shown in purple and blue, respectively. (B) Three alternative estimates of total protein per cell. 1. *light red*: Rescaling of total protein mass assuming a growth rate independent protein concentration and cell volumes estimated from Si *et al.* 2017. 2. *light green*: Rescaling of total protein mass using estimates of growth rate-dependent protein concentrations and cell volumes estimated from Si *et al.* 2017. Total protein per cell is calculated by assuming a 1.1 g/ml cellular mass density, 30% dry mass, with 90% of the dry mass corresponding to DNA, RNA, and protein ([Basan \*et al.\*, 2015](#)). See Estimation of Total Protein Content per Cell for details on calculation. 3. *light purple*: Rescaling of total protein mass using the experimental measurements from Basan *et al.* 2015.

**1097 Effect of cell volume on reported absolute protein abundances**

**1098** As noted in Experimental Details Behind Proteomic Data, the authors from the work in *Schmidt et al. (2016)* calculated proteome-wide protein abundances by first determining absolute abundances of 41 pre-selected proteins, which relied on adding synthetic heavy reference peptides into their protein samples at known abundance. This absolute quantitation was performed in replicate for each growth condition. Separately, the authors also performed a more conventional mass spectrometry measurement for samples from each growth condition, which attempted to maximize the number of quantified proteins but only provided relative abundances based on peptide intensities. Finally, using their 41 proteins with absolute abundances already determined, they then created calibration curves with which to relate their relative intensity to absolute protein abundance for each growth condition. This allowed them to estimate absolute protein abundance for all proteins detected in their proteome-wide data set. Combined with their flow cytometry cell counts, they were then able to determine absolute abundance of each protein detected on a per cell basis.

**1109** While this approach provided absolute abundances, another necessary step to arrive at total cellular protein was to account for any protein loss during their various protein extraction steps. Here the authors attempted to determine total protein separately using a BCA protein assay. In personal communications, it was noted that determining reasonable total protein abundances by BCA across their array of growth conditions was particularly troublesome. Instead, they noted confidence in their total protein measurements for cells grown in M9 minimal media + glucose and used this as a reference point with which to estimate the total protein for all other growth conditions.

**1116** For cells grown in M9 minimal media + glucose an average total mass of  $M_p = 240$  fg per cell was measured. **1117** Using their reported cell volume, reported as  $V_{orig} = 2.84$  fl, a cellular protein concentration of  $[M_p]_{orig} = M_p/V_{orig} = 85$  fg/fl. Now, taking the assumption that cellular protein concentration is relatively independent of growth rate, **1119** they could then estimate the total protein mass for all other growth conditions from,

$$M_{p\_i} = [M_p]_{orig} \cdot V_i \quad (8)$$

**1120** where  $M_p$  represents the total protein mass per cell and  $V_i$  is the cell volume for each growth condition  $i$  as measured in Volkmer and Heinemann, 2011. Here the thinking is that the values of  $M_p$  reflects the total cellular protein for growth condition  $i$ , where any discrepancy from their absolute protein abundance is assumed to be due to protein loss during sample preparation. The protein abundances from their absolute abundance measurements noted above were therefore scaled to their estimates and are shown in Figure *Figure 18* (purple data points).

**1125** If we instead consider the cell volumes predicted in the work of Si *et al.*, we again need to take growth in M9 minimal media + glucose as a reference with known total mass, but we can follow a similar approach to estimate **1127** total protein mass for all other growth conditions. Letting  $V_{Si\_glu} = 0.6$  fl be the predicted cell volume, the cellular **1128** protein concentration becomes  $[M_p]_{Si} = M_p/V_{Si\_glu} = 400$  fg/fl. The new total protein mass per cell can then be **1129** calculated from,

$$M'_{p\_i} = [M_p]_{Si} \cdot V_{Si\_i} \quad (9)$$

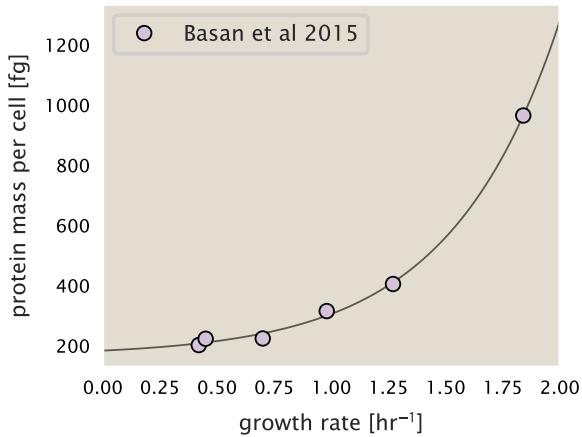
**1130** where  $M'_p$  is the new protein mass prediction, and  $V_{Si\_i}$  refers to the new volume prediction for each condition  $i$ . **1131** These are shown as red data points in Figure *Figure 18(B)*.

**1132 Relaxing assumption of constant protein concentration across growth conditions**

**1133** We next relax the assumption that cellular protein concentration is constant and instead, attempt to estimate **1134** it using experimental data. Here we use the estimation of total protein mass per cell detailed in Estimation of **1135** Total Protein Content per Cell for all data points in the *Schmidt et al. (2016)* data set. The green data points in **1136** *Figure 18(B)* show this prediction, and this represents the approach used to estimate total protein per cell for all **1137** data sets.

**1138 Comparison with total protein measurements from Basan *et al.* 2015.**

**1139** One of the challenges in our estimates in the preceding sections is the need to estimate protein concentration **1140** and cell volumes. These are inherently difficult to measure accurately due to the small size of *E. coli*. Indeed, for all



**Figure 19. Total cellular protein reported in Basan *et al.* 2015.** Measured protein mass as a function of growth rate as reproduced from Basan *et al.* 2015, with cells grown under different levels of nutrient limitation. The data was fit to an exponential curve where protein mass in fg per cell is given by  $14.65 e^{2.180 \cdot \lambda} + 172$  fg per cell, where  $\lambda$  is the growth rate in  $hr^{-1}$ .

the additional measurements of cell volume included in Figure [Figure 17](#), no measurements were performed for cells growing at rates below  $0.5\ hr^{-1}$ . It therefore remains to be determined whether our extrapolated cell volume estimates are appropriate, with the possibility that the logarithmic scaling of cell size might break down for slower growth.

In our last approach we therefore attempt to estimate total protein using experimental data that required no estimates of concentration or cell volume. Specifically, in the work of Basan *et al.*, the authors measured total protein per cell for a broad range of growth rates (reproduced in Figure [Figure 19](#)). These were determined by first measuring bulk protein from cell lysate, measured by the colorimetric Biuret method ([You \*et al.\* \(2013\)](#)), and then abundance per cell was calculated from cell counts from either plating cells or a Coulter counter. While it is unclear why Schmidt *et al.* was unable to take a similar approach, the results from Basan *et al* appear more consistent with our expectation that cell mass will increase exponentially with faster growth rates. In addition, although they do not consider growth rates below about  $0.5\ hr^{-1}$ , it is interesting to note that the protein mass per cell appears to plateau to a minimum value at slow growth. In contrast, our estimates using cell volume so far have predicted that total protein mass should continue to decrease slightly for slower growing cells. By fitting this data to an exponential function dependent on growth rate, we could then estimate the total protein per cell for each growth condition considered by [Schmidt \*et al.\* \(2016\)](#). These are plotted as red data points in [Figure 18\(B\)](#).

### Calculation of Complex Abundance

All protein data quantified the abundance of individual proteins per cell. However, this work requires estimates on the abundance of individual protein *complexes*, rather than the copy number of individual proteins. In our analysis of the protein copy number data, it became clear that the reported copy numbers do not always align with those based on reported stoichiometry. As one example of this, the F-O subunit of ATP synthase consists of three protein subunits with a stoichiometry of  $[AtpB][AtpF]_2[AtpE]_{10}$  (also referred to as subunits a, b, and c, respectively). In the experimental data of [Schmidt \*et al.\* \(2016\)](#), the values deviate from this quite substantially, with approximately 1000 AtpB, 9000 AtpF, and 300 AtpE reported per cell (minimal media + glucose growth condition). This highlights the technical challenges that still remain in our ability to quantify cellular composition, particularly for membrane-bound proteins like the ATP synthase complex considered here. In this section, we outline the approach we used to annotate proteins as part of each macromolecular complex and how we used averaging across the individual protein measurements to estimate an absolute complex abundances per cell.

Protein complexes, and proteins individually, often have a variety of names, both longform and shorthand. As individual proteins can have a variety of different synonyms, we sought to ensure that each protein annotated in the data sets used the same synonym. To do use, we relied heavily on the EcoCyc Genomic Database ([Keseler](#)

1172 *et al., 2017*). Each protein in available data sets included an annotation of one of the gene name synonyms as  
1173 well as an accession ID – either a UniProt or Blattner "b-number". We programmatically matched up individual  
1174 accession IDs between the proteins in different data sets. In cases where accession IDs matched but the gene  
1175 names were different, we manually verified that the gene product was the same between the datasets and chose  
1176 a single synonym. All code used in the data cleaning and unification procedures can be found on the associated  
1177 [GitHub repository] (DOI:XXX) associated with this paper as well as on the associated [paper website](#).

1178 With each protein conforming to a single identification scheme, we then needed to identify the molecular  
1179 complexes each protein was a member of. Additionally, we needed to identify how many copies of each protein  
1180 were present in each complex (i.e. the subunit copy number) and compute the estimated abundance complex  
1181 that accounted for fluctuations in subunit stoichiometry. To map proteins to complexes, we accessed the EcoCyc  
1182 *E. coli* database *Keseler et al. (2017)* using PathwayTools version 23.0 *Karp et al. (2019)*. With a license for PathWay  
1183 Tools, we mapped each unique protein to its annotated complexes via the BioCyc Python package. As we mapped  
1184 each protein with *all* of its complex annotations, there was redundancy in the dataset. For example, ribosomal  
1185 protein L20 (RplT) is annotated to be a component of the 50S ribosome (EcoCyc complex CPLX-03962) as well as a  
1186 component of the mature 70S ribosome (EcoCyc complex CPLX-03964).

1187 In addition to the annotated complex, we collected information on the stoichiometry of each macromolecular  
1188 complex. For a complex with  $N_{\text{subunits}}$  protein species, for each protein subunit  $i$  we first calculate the number of  
1189 complexes that *could* be formed given the measured protein copy numbers per cell,

$$N_{\text{complex}}(\text{subunit } i) = \frac{P_{\text{subunit } i}^{(\text{measured})}}{m_{\text{subunit } i}}. \quad (10)$$

1190 Here,  $P_{\text{subunit } i}^{(\text{measured})}$  refers to the measured protein copy number of species  $i$ , and  $m$  refers to the number of monomers  
1191 present for that protein in the complex. For example, the 70S mature ribosome complex has 55 protein compo-  
1192 nents, all of which are present in a single copy except L4 (RplL), which is present in 4 copies ( $m = 4$ ). For each  
1193 ribosomal protein, we then calculate the maximum number of complexes that could be formed using [Equation 10](#).  
1194 This example, along with example from 5 other macromolecular complexes, can be seen in [Figure 20](#).

1195 It is important to note that measurement noise, efficiency of protein extraction, and differences in protein  
1196 stability will mean that the precise value of each calculation will be different for each component of a given complex.  
1197 Thus, to report the total complex abundance, we use the arithmetic mean of across all subunits in the complex,

$$\langle N_{\text{complex}} \rangle = \frac{1}{N_{\text{subunits}}} \sum_i^{N_{\text{subunits}}} \frac{P_i^{(\text{measured})}}{m_{\text{subunit } i}}. \quad (11)$$

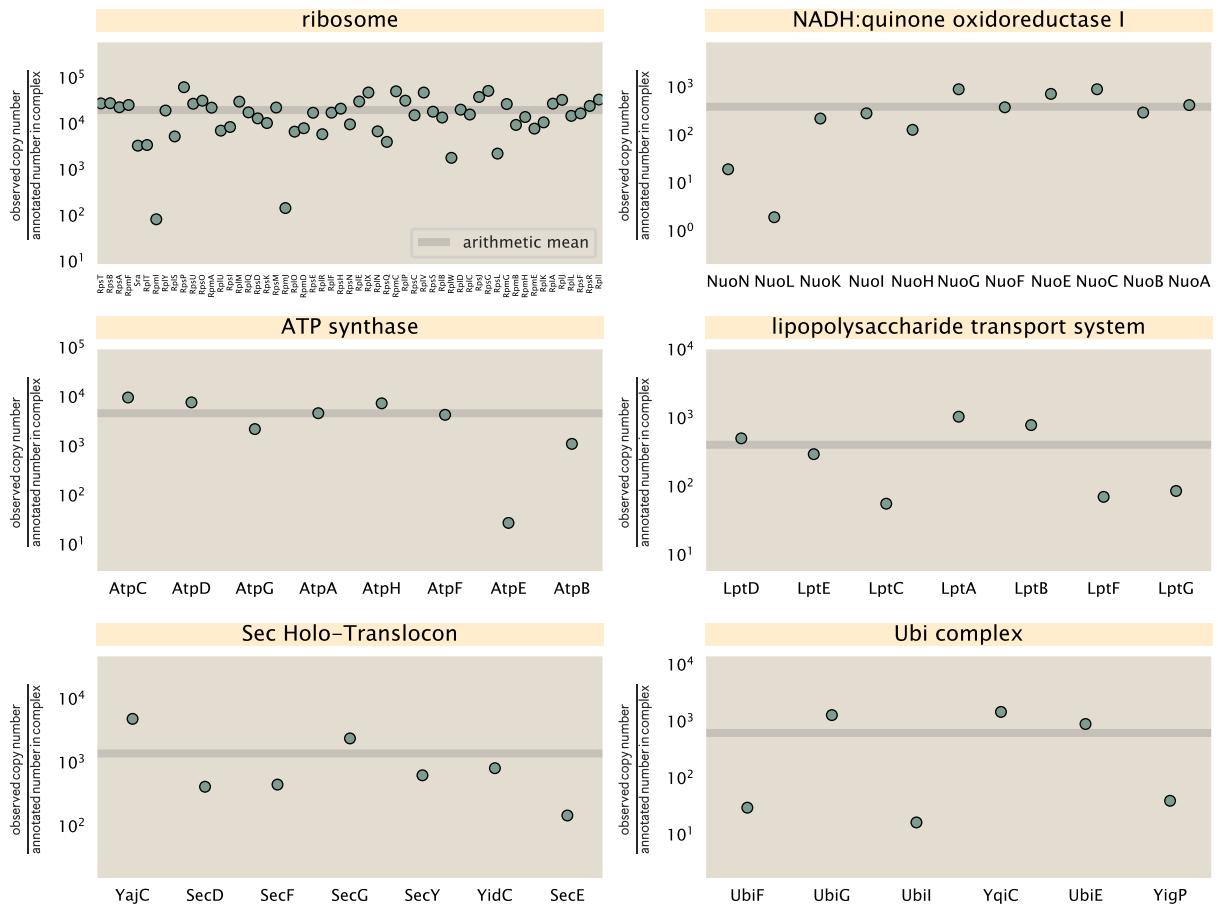
1198 in [Figure 20](#), we show this mean value as a grey line for a variety of different complexes. Additionally, we have  
1199 built an interactive figure accessible on the [paper website](#) where the validity of this approach can be examined  
1200 for any complex with more than two subunits (thus, excluding monomers and dimers).

## 1201 Extending Estimates to a Continuum of Growth Rates

1202 In the main text, we considered a standard stopwatch of 5000 s to estimate the abundance of the various protein  
1203 complexes considered. In addition to point estimates, we also showed the estimate as a function of growth rate  
1204 as transparent grey curves. In this section, we elaborate on this continuum estimate, giving examples of estimates  
1205 that scale with either cell volume, cell surface area, or number of origins of replication.

## 1206 Estimation of the total cell mass

1207 For many of the processes estimated in the main text we relied on a cellular dry mass of  $\approx 300$  fg from which we  
1208 computed elemental and protein fractions using knowledge of fractional composition of the dry mass. At modest  
1209 growth rates, such as the 5000 s doubling time used in the main text, this is a reasonable number to use as the  
1210 typical cell mass is  $\approx 1$  pg and *E. coli* cells can approximated as 70% water by volume. However, as we have shown  
1211 in the preceding sections, the cell size is highly dependent on the growth rate. This means that a dry mass of 300  
1212 fg cannot be used reliably across all growth rates.



**Figure 20. Calculation of the mean complex abundance from measurements of single subunits.** Six of the largest complexes (by number of subunits) in *E. coli*. Points correspond to the maximum number of complexes that can be formed given measurement of that individual protein. Solid grey line corresponds to the arithmetic mean across all subunits. These data correspond to measurements from *Schmidt et al. (2016)* in a glucose-supplemented minimal growth medium.

1213 Rather, using the phenomenological description of cell volume scaling exponentially with growth rate, and  
1214 using a rule-of-thumb of a cell buoyant density of  $\approx 1.1 \text{ pg} / \text{fL}$  (BNID: 103875), we can calculate the cell dry mass  
1215 across a range of physiological growth rates as

$$m_{\text{cell}} \approx \rho V(\lambda) \approx \rho a e^{\lambda * b} \quad (12)$$

1216 where  $a$  and  $b$  are constants with units of  $\mu\text{m}^3$  and hr, respectively. The value of these constants can be estimated  
1217 from the careful volume measurements performed by *Si et al.* (2017,?), as considered in Appendix Estimation of  
1218 Cell Size and Surface Area earlier.

### 1219 Complex Abundance Scaling With Cell Volume

1220 Several of the estimates performed in the main text are implicitly dependent on the cell volume. This includes  
1221 processes such as ATP utilization and, most prominently, the transport of nutrients, whose demand will be pro-  
1222 portional to the volume of the cell. Of the latter, we estimated the number of transporters that would be needed  
1223 to shuttle enough carbon, phosphorus, and sulfur across the membrane to build new cell mass. To do so, we  
1224 used elemental composition measurements combined with a 300 fg cell dry mass to make the point estimate. As  
1225 we now have a means to estimate the total cell mass as a function of volume, we can generalize these estimates  
1226 across growth rates.

1227 Rather than discussing the particular details of each transport system, we will derive this scaling expression in  
1228 very general terms. Consider that we wish to estimate the number of transporters for some substance  $X$ , which  
1229 has been measured to be made up some fraction of the dry mass,  $\theta_X$ . If we assume that, irrespective of growth  
1230 rate, the cell dry mass is relatively constant (*Basan et al.*, 2015) and  $\approx 30\%$  of the total cell mass, we can state that  
1231 the total mass of substance  $X$  as a function of growth rate is

$$m_X \approx 0.3 \times \rho V(\lambda) \theta_X, \quad (13)$$

1232 where we have used  $\rho V(\lambda)$  as an estimate of the total cell mass, defined in *Equation 12*. To convert this to the  
1233 number of units  $N_X$  of substance  $X$  in the cell, we can use the formula weight  $w_X$  of a single unit of  $X$  in conjunction  
1234 with *Equation 13*,

$$N_X \approx \frac{m_X}{w_X}. \quad (14)$$

1235 To estimate the number of transporters needed, we make the approximation that loss of units of  $X$  via diffusion  
1236 through porins or due to the permeability of the membrane is negligible and that a single transporter complex  
1237 can transport substance  $X$  at a rate  $r_X$ . As this rate  $r_X$  is in units of  $X$  per time per transporter, we must provide  
1238 a time window over which the transport process can occur. This is related to the cell doubling time  $\tau$ , which can  
1239 be calculated from the the growth rate  $\lambda$  as  $\tau = \log(2)/\lambda$ . Putting everything together, we arrive at a generalized  
1240 transport scaling relation of

$$N_{\text{transporters}}(\lambda) = \frac{0.3 \times \rho V(\lambda) \theta_X}{w_X r_X \tau}. \quad (15)$$

1241 This function is used to draw the continuum estimates for the number of transporters seen in Figures 2 and  
1242 3 as transparent grey curves. Occasionally, this continuum scaling relationship will not precisely agree with the  
1243 point estimate outlined in the main text. This is due to the choice of  $\approx 300 \text{ fg}$  total dry mass per cell for the point  
1244 estimate, whereas we considered more precise values of cell mass in the continuum estimate. We note, however,  
1245 that both this scaling relation and the point estimates are meant to describe the order-of-magnitude observed,  
1246 and not the predict the exact values of the abundances.

1247 *Equation 15* is a very general relation for processes where the cell volume is the "natural variable" of the  
1248 problem. This means that, as the cell increases in volume, the requirements for substance  $X$  also scale with  
1249 volume rather than scaling with surface area, for example. So long as the rate of the process, the fraction of the  
1250 dry mass attributable to the substance, and the formula mass of the substance is known, *Equation 15* can be used  
1251 to compute the number of complexes needed. For example, to compute the number of ATP synthases per cell,  
1252 *Equation 15* can be slightly modified to the form

$$N_{\text{ATP synthases}}(\lambda) = \frac{0.3 \times \rho V(\lambda) \theta_{\text{protein}} N_{\text{ATP}}}{w_{\text{AA}} r_{\text{ATP}} \tau}, \quad (16)$$

1253 where we have included the term  $N_{ATP}$  to account for the number of ATP equivalents needed per amino acid for  
 1254 translation ( $\approx 4$ , BNID: 114971), and  $w_{AA}$  is the average mass of an amino acid. The grey curves in Figure 4 of the  
 1255 main text were made using this type of expression.

## 1256 A Relation for Complex Abundance Scaling With Surface Area

1257 In our estimation for the number of complexes needed for lipid synthesis and peptidoglycan maturation, we used  
 1258 a particular estimate for the cell surface area ( $\approx 5 \mu m$ , BNID: 101792) and the fraction of dry mass attributable to  
 1259 peptidoglycan ( $\approx 3\%$ , BNID: 101936). Both of these values come from glucose-fed *E. coli* in balanced growth. As we  
 1260 are interested in describing the scaling as a function of the growth rate, we must also consider how these values  
 1261 scale with cell surface area, which is the natural variable for these types of processes. In the coming paragraphs,  
 1262 we highlight how we incorporate a condition-dependent surface area into our calculation of the number of lipids  
 1263 and murein monomers that need to be synthesized and crosslinked, respectively.

### 1264 Number of Lipids

1265 To compute the number of lipids as a function of growth rate, we make the assumption that some features, such as  
 1266 the surface area of a single lipid ( $A_{lipid} \approx 0.5 \text{ nm}^2$ , BNID: 106993) and the total fraction of the membrane composed  
 1267 of lipids ( $\approx 40\%$ , BNID: 100078) are independent of the growth rate. Using these approximations combined with  
 1268 **Equation 6**, and recognizing that each membrane is composed of two leaflets, we can compute the number of  
 1269 lipids as a function of growth rate as

$$N_{lipids}(\lambda) \approx \frac{4 \text{ leaflets} \times 0.4 \times \eta \pi \left( \frac{\eta \pi}{4} - \frac{\pi}{12} \right)^{-2/3} V(\lambda)^{2/3}}{A_{lipid}} \quad (17)$$

1270 where  $\eta$  is the length-to-width aspect ratio and  $V$  is the cell volume.

### 1271 Number of Murein Monomers

1272 In calculation of the number of transpeptidases needed for maturation of the peptidoglycan, we used an empirical  
 1273 measurement that  $\approx 3\%$  of the dry mass is attributable to peptidoglycan and that a single murien monomer is  
 1274  $m_{murein} \approx 1000 \text{ Da}$ . While the latter is independent of growth rate, the former is not. As the peptidoglycan exists as  
 1275 a thin shell with a width of  $w \approx 10 \text{ nm}$  encapsulating the cell, one would expect the number of murein monomers  
 1276 scales with the surface area of this shell. In a similar spirit to our calculation of the number of lipids, the total  
 1277 number of murein monomers as a function of growth rate can be calculated as

$$N_{murein \text{ monomers}}(\lambda) \approx \frac{\rho_{pg} w \eta \pi \left( \frac{\eta \pi}{4} - \frac{\pi}{12} \right)^{-2/3} V(\lambda)^{2/3}}{m_{murein}}, \quad (18)$$

1278 where  $\rho_{pg}$  is the density of peptidoglycan.

## 1279 Complex Abundance Scaling With Number of Origins, and rRNA Synthesis

1280 While the majority of our estimates hinge on the total cell volume or surface area, processes related to the central  
 1281 dogma, namely DNA replication and synthesis of rRNA, depend on the number of chromosomes present in the  
 1282 cell. As discussed in the main text, the ability of *E. coli* to parallelize the replication of its chromosome by having  
 1283 multiple active origins of replication is critical to synthesize enough rRNA, especially at fast growth rates. Derived  
 1284 in *Si et al. (2017)* and reproduced in the main text and Appendix Estimation of  $\langle \#ori \rangle / \langle \#ter \rangle$  and  $\langle \#ori \rangle$  below, the  
 1285 average number of origins of replication at a given growth rate can be calculated as

$$\langle \#ori \rangle \approx 2^{t_{cyc} \lambda / \ln 2} \quad (19)$$

1286 where  $t_{cyc}$  is the total time of replication and division. We can make the approximation that  $t_{cyc} \approx 70 \text{ min}$ , which is  
 1287 the time from the initiation of chromosomal replication until division. This time corresponds to the sum of the so-  
 1288 called C and D periods of the cell cycle, which correspond to the time it takes to replicate the entire chromosome  
 1289 (C period) and the time from completion to eventual division (D period) *Helmstetter and Cooper (1968)*.

1290 In the case of rRNA synthesis, the majority of the rRNA operons are surrounding the origin of replication. Thus,  
1291 at a given growth rate  $\lambda$ , the average dosage of rRNA operons per cell  $D_{\text{rRNA}}$  is

$$D_{\text{rRNA}}(\lambda) \approx N_{\text{rRNA operons}} \times 2^{t_{\text{cyc}}\lambda / \ln 2}. \quad (20)$$

1292 This makes the approximation that *all* rRNA operons are localized around the origin. In reality, the operons  
1293 are some distance away from the origin, making **Equation 20** an approximation (*Dennis et al., 2004*).

1294 In the main text, we stated that at a growth rate of  $0.5 \text{ hr}^{-1}$ , there is  $\approx 1$  chromosome per cell. While a fair  
1295 approximation, **Equation 19** illustrates that is not precisely true, even at slow growth rates. In estimating the  
1296 number of RNA polymerases as a function of growth rate, we consider that regardless of the number of rRNA  
1297 operons, they are all sufficiently loaded with RNA polymerase such that each operon produces one rRNA per  
1298 second. Thus, the total number of RNA polymerase as a function of the growth rate can be calculated as

$$N_{\text{RNA polymerase}}(\lambda) \approx L_{\text{operon}} D_{\text{rRNA}} \rho_{\text{RNA polymerase}}, \quad (21)$$

1299 where  $L_{\text{operon}}$  is the total length of an rRNA operon ( $\approx 4500 \text{ bp}$ ) and  $\rho_{\text{RNA polymerase}}$  is packing density of RNA poly-  
1300 merase on a given operon, taken to be 1 RNA polymerase per 80 nucleotides.

### 1301 Calculation of active ribosomal fraction.

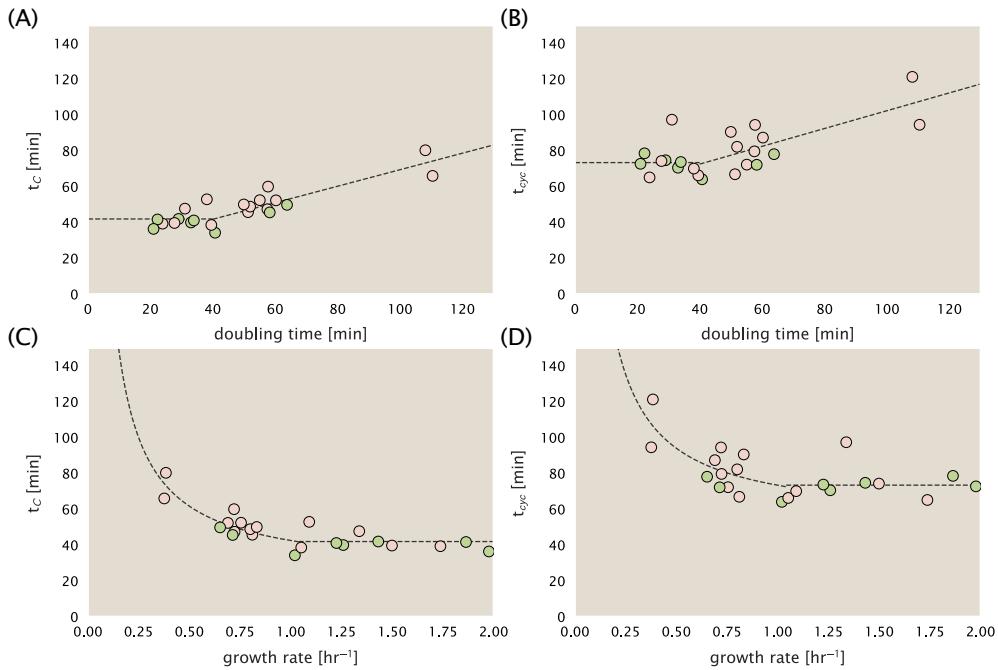
1302 In the main text we used the active ribosomal fraction  $f_a$  that was reported in the work of *Dai et al. (2016)* to  
1303 estimate the active ribosomal mass fraction  $\Phi_R \times f_a$  across growth conditions. We lacked any specific model to  
1304 consider how  $f_a$  should vary with growth rate, and instead find that the data is well-approximated by fitting to an  
1305 exponential curve ( $f_a = -0.889 e^{4.6 \cdot \lambda} + 0.922$ ; dashed line in inset of **Figure 9(C)**). We use this function to estimate  $f_a$   
1306 for each of the data points shown in **Figure 9(C)**.

### 1307 Estimation of $\langle \#ori \rangle / \langle \#ter \rangle$ and $\langle \#ori \rangle$ .

1308 *E. coli* shows robust scaling of cell size with the average number of origins per cell,  $\langle \#ori \rangle$  (*Si et al., 2017*). Since  
1309 protein makes up a majority of the cell's dry mass, the change in cell size is also a reflection of the changes in  
1310 proteomic composition and total abundance across growth conditions. Given the potential constraints on rRNA  
1311 synthesis and changes in ribosomal copy number with  $\langle \#ori \rangle$ , it becomes important to also consider how pro-  
1312 tein copy numbers vary with the state of chromosomal replication. This is particularly true when trying to make  
1313 sense of the changes in ribosomal fraction and growth-rate dependent changes in proteomic composition at a  
1314 mechanistic level. As considered in the main text, it is becoming increasingly apparent that regulation through  
1315 the secondary messengers (p)ppGpp may act to limit DNA replication and also reduce ribosomal activity in poorer  
1316 nutrient conditions. In this context, both  $\langle \#ori \rangle$ , as well as the  $\langle \#ori \rangle / \langle \#ter \rangle$  ratio become important parameters  
1317 to consider and keep track of. An increase in  $\langle \#ori \rangle / \langle \# ter \rangle$  ratio in particular, causes a relatively higher gene  
1318 dosage in rRNA and r-protein genes due to skew in genes near the origin, where the majority of these are located

1319 In the main text we estimated the change in  $\langle \#ori \rangle$  with growth rate using the nutrient-limited wild-type cell  
1320 data from *Si et al. (2017)*. We consider their measurements of DNA replication time ( $t_C$ , 'C' period of cell division),  
1321 total cell cycle time ( $t_{\text{cyc}}$ , 'C' + 'D' period of cell division), and doubling time  $\tau$  from wild-type *E. coli* growing across  
1322 a range of growth conditions. Here we show how we estimate this parameter, as well as the  $\langle \#ori \rangle / \langle \# ter \rangle$  ratio  
1323 from their data. We begin by considering  $\langle \#ori \rangle$ . If the cell cycle time takes longer than the time of cell division, the  
1324 cell will need to initiate DNA replication more often than its rate of division,  $2^{\lambda t} = 2^{\ln(2) \cdot t / \tau}$  to maintain steady state  
1325 growth. Cells will need to do this in proportion to the ratio  $\lambda_{\text{cyc}} / \lambda = t_{\text{cyc}} / \tau$ , and the number of origins per cell (on  
1326 average) is then given by  $2^{t_{\text{cyc}} / \tau}$ . The average number of termini will in contrast depend on the lag time between  
1327 DNA replication and cell division,  $t_D$ , with  $\langle \#ori \rangle / \langle \# ter \rangle$  ratio =  $2^{t_{\text{cyc}} / \tau - t_D / \tau} = 2^{t_C / \tau}$ .

1328 In Figure 21(A) and (B) we plot the measured  $t_C$  and  $t_{\text{cyc}}$  values versus the doubling time from *Si et al. (2017)*.  
1329 The authors estimated  $t_C$  by marker frequency analysis using qPCR, while  $t_{\text{cyc}} = t_C + t_D$  were inferred from  $t_C$  and  
1330  $\tau$ . In the plots we see that both  $t_C$  and  $t_{\text{cyc}}$  reach a minimum at around 40 and 75 minutes, respectively. For a  
1331 C period of 40 minutes, this would correspond to a maximum rate of elongation of about 1,000 bp/sec. Since  
1332 we lacked a specific model to describe how each of these parameters vary with growth condition, we assumed  
1333 that they were linearly dependent on the doubling time. For each parameter,  $t_C$  and  $t_{\text{cyc}}$ , we split them up into



**Figure 21. Estimation of  $\langle \# \text{ori} \rangle / \langle \# \text{ter} \rangle$  and  $\langle \# \text{ori} \rangle$  using data from Si et al. (2017).** (A) and (B) plot the reported  $t_C$  and  $t_{cyc}$  as a function of cell doubling time  $\tau$ , respectively. The dashed lines show a piecewise fit to the data. For short doubling times (rich media),  $t_C$  and  $t_{cyc}$  are assumed constant ( $t_C = 42$  minutes,  $t_{cyc} = 73$  minutes). At the transition, taken to occur at 40 minutes, the dashed line corresponds to an assumed proportional increase in each parameter as a function of the doubling time ( $t_C = 0.46\tau + 23.3$  minutes,  $t_{cyc} = 0.50\tau + 52.7$  minutes). (C) and (D) plot the same data as in (A) and (B), but as a function of growth rate, given by  $\lambda = \ln(2)/\tau$ .

1334 two domains corresponding to poorer nutrient conditions and rich nutrient conditions (cut off at  $\tau \approx 40$  minutes  
 1335 where chromosomal replication becomes nearly constant). The fit lines are shown as solid black lines. In Figure  
 1336 21(C) and (D) we also show  $t_C$  and  $t_{cyc}$  as a function of growth rate  $\lambda$  along with our piecewise linear fits, which  
 1337 match the plots in the main text.

### 1338 Derivation of Minimal Model for Nutrient-Mediated Growth Rate Control

1339 Here we provide a derivation of the minimal model for growth rate control under nutrient-limited growth. By  
 1340 growth rate control, we are specifically referring to the ability of bacteria to modulate their proteome ( $N_{\text{pep}}$ ,  $R$ ,  $\Phi_R$ )  
 1341 and cell size as nutrient conditions change, with slower growing cells generally being smaller in size (Ojikic et al.,  
 1342 2019). This capability provides bacteria with a particular benefit when nutrients are more scarce since it will mean  
 1343 there is a smaller net demand on carbon, phosphorus, sulfur, and nitrogen. The specific goal of developing this  
 1344 model is to help us better explore the overall constraints on growth that follow from 1) our observation that many  
 1345 of the cellular processes we've considered require increased protein abundance at faster growth rates, and 2) a  
 1346 strict limit on growth rate that is governed by the ribosomal synthesis rate and ribosomal mass fraction  $\Phi_R$ .

1347 In Figure 11(A) of the main text we provide a schematic of the model, where we consider growth as simply  
 1348 governed by the rate of protein synthesis ( $r_t \times R \times f_a$ ). In order to grow rapidly, at least to the extent possible,  
 1349 these three parameters need to be maximized (with  $r_t \leq 17$  amino acids per second, and  $f_a \leq 1$  reported in the  
 1350 work of Dai et al. (2016)). The elongation rate  $r_t$  will depend on how quickly ribosomes can match codons with  
 1351 their correct amino-acyl tRNA, along with the subsequent steps of peptide bond formation and translocation. This  
 1352 ultimately depends on the cellular concentration amino acids, which we treat as a single effective species,  $[AA]_{\text{eff}}$ .

1353 In our model, we need to determine the rate of peptide elongation  $r_t$ , which we consider as simply depending  
 1354 on the supply of amino acids (and, therefore, also amino-acyl tRNAs) through a parameter  $r_{AA}$  in units of AA per  
 1355 second, and the rate of amino acid consumption by protein synthesis ( $r_t \times R \times f_a$ ). The balance between these  
 1356 two rates will determine the effective amino acid concentration in the cell  $[AA]_{\text{eff}}$ . An important premise for this

1357 formulation is growing evidence that cells are able to modulate their biosynthesis activity according to nutrient  
 1358 availability (i.e. extent of chromosomal replication, transcriptional, and translation activity) through secondary-  
 1359 messenger molecules like (p)ppGpp (**Hauryliuk et al., 2015; Zhu and Dai, 2019; Kraemer et al., 2019; Fernández-**  
 1360 **Coll et al., 2020; Büke et al., 2020**). Given our observation that protein synthesis and energy production are  
 1361 not limiting, we assume that other molecular players required by ribosomes like elongation factors and GTP are  
 1362 available in sufficient abundance. In addition, experimentally, the relative number of tRNA and elongation factor  
 1363 EF-Tu per ribosome have been found to increase in poorer nutrient conditions **Pedersen (1978); Dong et al. (1996);**  
 1364 **Klumpp et al. (2013)**).

1365 We begin by considering a coarse-grained description of peptide elongation, which includes 1) the time re-  
 1366 quired to find and bind each correct amino-acyl tRNA, and 2) the remaining steps in peptide elongation that will  
 1367 not depend on the amino acid availability. These time scales will be related to the inverse of the elongation rate  
 1368  $r_t$ ,

$$\frac{1}{r_t} = \frac{1}{k_{on}\alpha[AA]_{eff}} + \frac{1}{r_t^{max}}. \quad (22)$$

1369 where we have assumed that the rate of binding by amino-acyl tRNA  $k_{on}$  is proportional to  $[AA]_{eff}$  by a constant  
 1370  $\alpha$ .  $r_t^{max}$  refers to the maximum elongation rate. This leads to a Michaelis-Menten dependence of the elongation  
 1371 rate  $r_t$  on the effective amino acid concentration  $[AA]_{eff}$  (**Klumpp et al., 2013; Dai et al., 2016**). We can re-write this  
 1372 more succinctly in terms of an effective dissociation constant,

$$K_D = \frac{r_t^{max}}{\alpha k_{on}}, \quad (23)$$

1373 where the elongation rate  $r_t$  is now given by

$$r_t = \frac{r_t^{max}}{1 + K_D/[AA]_{eff}}. \quad (24)$$

1374 The rate of amino acid supply  $r_{AA}$  will vary with changing nutrient conditions and the cell can maintain  $[AA]_{eff}$   
 1375 by tuning the rate of amino acid consumption,  $r_t \times R \times f_a$ . Thus,  $[AA]_{eff}$  is determined by the difference in the  
 1376 rate of amino acid synthesis (or import, for rich media) and/or tRNA charging,  $r_{AA}$ , and the rate of consumption,  
 1377  $r_t \times R \times f_a$ . Over an arbitrary length of time  $t$  of cellular growth, the cell will grow in volume, requiring us to consider  
 1378 these rates in terms of concentration rather than absolute numbers, with  $[AA]_{eff}$  given by,

$$\int_0^t \frac{d[AA]_{eff}}{dt} dt = \int_0^t ([r_{AA}] - [r_t \times R \times f_a]) dt. \quad (25)$$

1379 This considers the net change in amino acid concentration over a time from 0 to  $t$ , with the square brackets  
 1380 indicating concentrations per unit time. Integrating **Equation 25** yields.

$$[AA]_{eff} = t([r_{AA}] - [r_t \times R \times f_a]). \quad (26)$$

1381 Alternatively, to connect to the experimental data in terms of absolute ribosome copy number  $R$  we can con-  
 1382 sider a unit volume  $V$ ,

$$[AA]_{eff} = \frac{t(r_{AA} - r_t \times R \times f_a)}{V \times N_A}, \quad (27)$$

1383 where  $r_{AA}$  is in units of AA per unit time and  $r_t$  is in units of AA per unit time per ribosome.  $N_A$  refers to Avogadro's  
 1384 number and is needed to convert between concentration and absolute numbers per cell. With an expression for  
 1385  $[AA]_{eff}$  in hand, we can now solve **Equation 24** for  $r_t$ , which is a quadratic function with a physically-meaningful  
 1386 root of

$$r_t = \frac{t(r_{AA} + r_t^{max}Rf_a) + K_DVN_A - \sqrt{(r_{AA} + r_t^{max}Rf_a)^2 + 4(Rf_a)(r_t^{max}r_{AA})}}{2Rf_a}. \quad (28)$$

1387 This is the key equation that allows us to calculate growth rate for any combination of  $N_{pep}$ ,  $R$ ,  $f_a$ , and cell size  $V$   
 1388 as a function of amino acid supply  $r_{AA}$  (**Equation 3** of the main text). We refer the reader to A Minimal Model of

1389 Nutrient-Mediated Growth Rate Control of the main text for our exploration of this model in the context of the  
1390 proteomic data.

1391 We end this section by noting several distinctions of this formulation with previous work. The first, as noted  
1392 in the main text, relates to the now seminal work of *Scott et al. (2010)*, which provides a treatment of resource  
1393 allocation that partitions of the proteome into sectors – including one for ribosome-associated proteins and one  
1394 for metabolic proteins. As cells grow faster, there is a notable change in the mass fraction of these sectors, with an  
1395 increase in ribosomal content that is predominantly achieved at the expense of a decrease in the metabolic sector.  
1396 By including an additional constraint through the phenomenological parameter  $v$ , which characterizes the quality  
1397 of the growth medium *Scott et al. (2010); Klumpp et al. (2013); Klumpp and Hwa (2014)*, the authors derive a model  
1398 of growth rate, dependent on optimal resource allocation. Here we have developed a model that considers the  
1399 effect of changes in absolute protein abundance and ribosomal content, and consider how these influence the  
1400 achievable growth rate. In addition, by accounting for the metabolic supply of amino acids directly though their  
1401 availability in the cell (i.e.  $[AA]_{\text{eff}}$ ), we are able to consider how the balance between translation-specific metabolic  
1402 capacity and translational capacity influences both the elongation rate  $r_e$  and growth rate  $\lambda$ .

1403 The second and last point we note is that the recent works from *Dai et al. (2016)* and *Klumpp et al. (2013)* also  
1404 employ a similar coarse-graining of translation elongation as we've considered above. Here, however, a notable  
1405 distinction is that the authors consider the entire ternary complex (i.e. the complex of amino-acyl tRNA, EF-Tu,  
1406 and GTP) as rate limiting. Further, through an assumed proportionality between ternary complex and ribosome  
1407 abundance, they arrive at a formulation of elongation rate  $r_e$  that exhibits a Michaelis-Menten dependence on  
1408 the ribosomal fraction  $\Phi_R$ . They demonstrate that all their measurements of elongation rate, even upon addition  
1409 of sublethal doses of chloramphenicol (which cause an increase in both  $r_e$  and  $\Phi_R$ ), can be collapsed onto a sin-  
1410 gle curve described by this Michaelis-Menten dependence. There is always a benefit to increase their ribosomal  
1411 fraction  $\Phi_R$  on growth rate when nutrient conditions allow (see Maximum Growth Rate is Determined by the Ri-  
1412 bosomal Mass Fraction), and this trend in the data in part follows from the tendency for cells to increase  $\Phi_R$  and  
1413 better maximize  $r_e$  as nutrient conditions improve. In addition, it does not account for the decrease in the frac-  
1414 tion of actively translating ribosome  $f_a$  that was strikingly apparent at slow growth rates or in sublethal doses of  
1415 chloramphenicol in the work of *Dai et al. (2016)*. Through **Equation 28** we also account for changes in the fraction  
1416 of actively translating ribosomes. Ultimately, we find that cells are able to maximize both  $\Phi_R$ ,  $r_e$ , and their growth  
1417 rate only to the extent allowed by the nutrient conditions (i.e. via  $r_{AA}$ ) and through the maintenance of the cellular  
1418 pool of amino acids  $[AA]_{\text{eff}}$ , amino-acyl tRNA, GTP, as well as the synthesis of other key molecular constituents like  
1419 EF-Tu.

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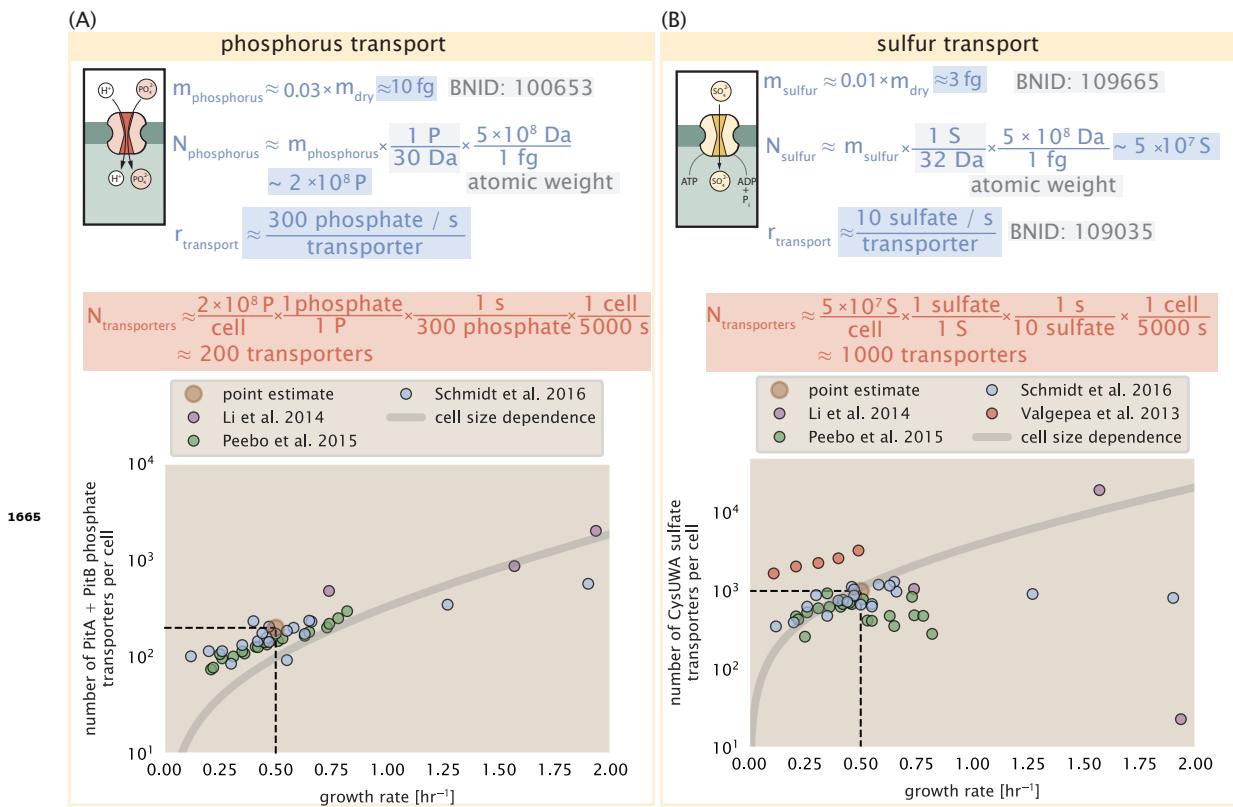
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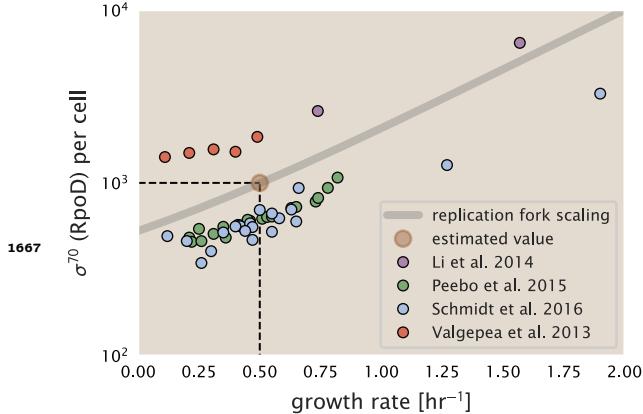
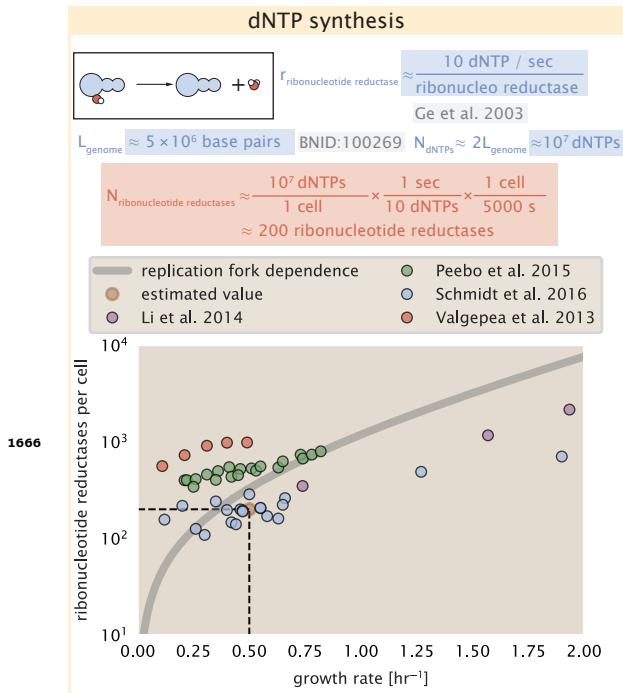
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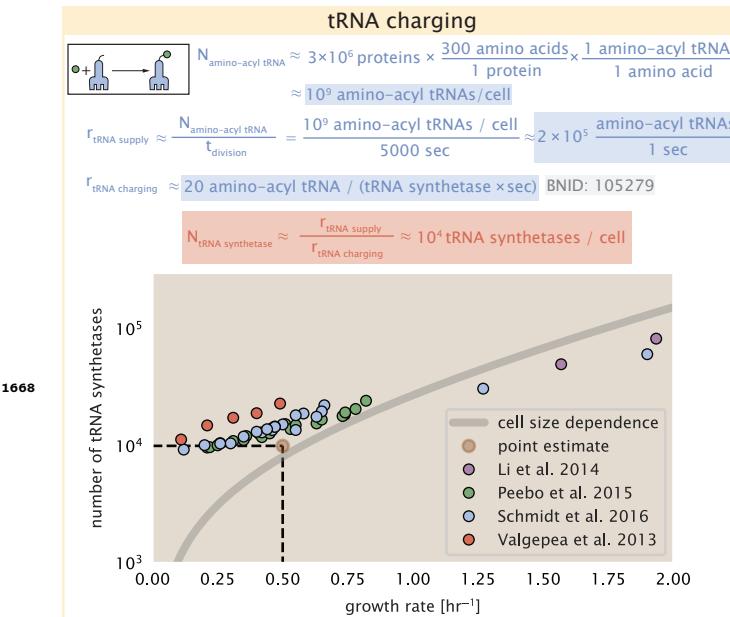
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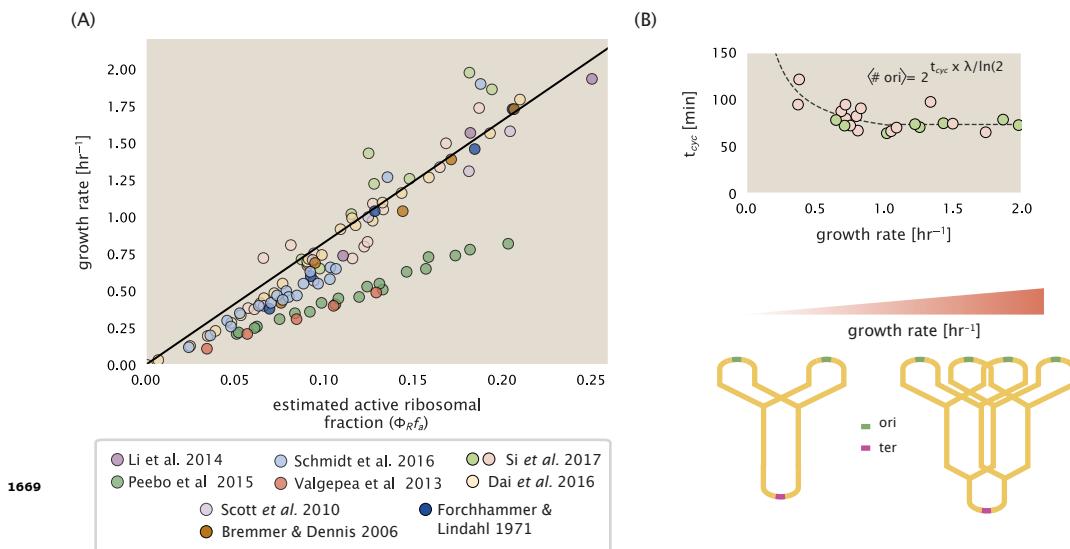


**Figure 2-Figure supplement 1.** (A) Estimate for the number of PitA phosphate transport systems needed to maintain a 3% phosphorus *E. coli* dry mass. Points in plot correspond to the total number of PitA transporters per cell. (B) Estimate of the number of CysUWA complexes necessary to maintain a 1% sulfur *E. coli* dry mass. Points in plot correspond to average number of CysUWA transporter complexes that can be formed given the transporter stoichiometry [CysA]<sub>2</sub>[CysU][CysW][Sbp/CysP]. Grey line in (A) and (B) represents the estimated number of transporters per cell at a continuum of growth rates.

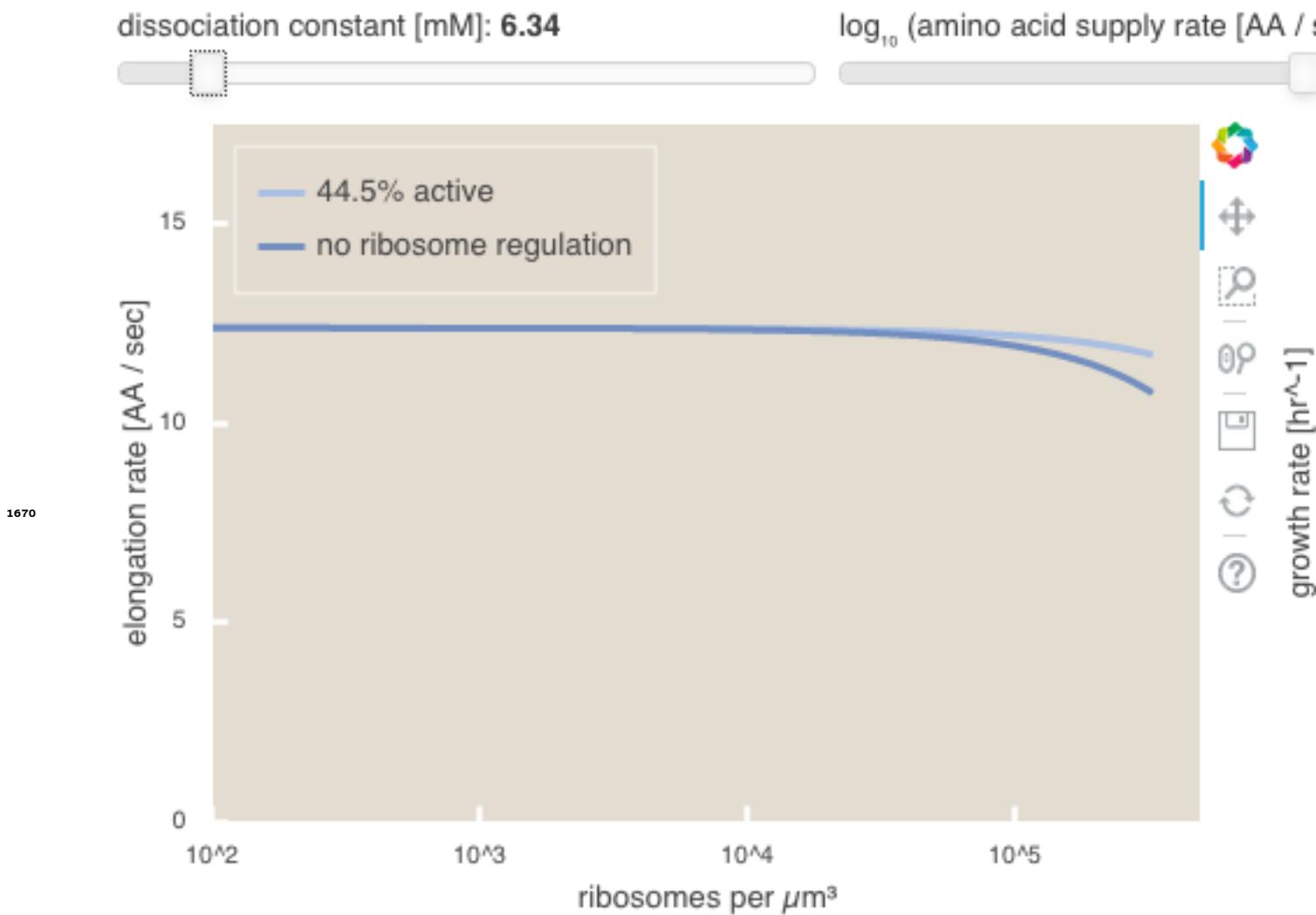




**Figure 8-Figure supplement 1.** Estimation for the number of tRNA synthetases that will supply the required amino acid demand. The sum of all tRNA synthetases copy numbers are plotted as a function of growth rate ([ArgS], [CysS], [GlnS], [GltX], [IleS], [LeuS], [ValS], [AlaS]<sub>2</sub>, [AsnS]<sub>2</sub>, [AspS]<sub>2</sub>, [TyrS]<sub>2</sub>, [TrpS]<sub>2</sub>, [ThrS]<sub>2</sub>, [SerS]<sub>2</sub>, [ProS]<sub>2</sub>, [PheS]<sub>2</sub>[PheT]<sub>2</sub>, [MetG]<sub>2</sub>, [lysS]<sub>2</sub>, [HisS]<sub>2</sub>, [GlyS]<sub>2</sub>[GlyQ]<sub>2</sub>].



**Figure 9-Figure supplement 1.** (A) Actively translating ribosomal fraction versus growth rate. The actively translating ribosomal fraction is calculated using the estimated values of  $f_a$  from [Dai et al. \(2016\)](#) (shown in inset; see the Appendix Section "Calculation of active ribosomal fraction" for additional detail). Additional measurements in addition to the proteomic measurements are based on measurements of cellular RNA to protein ratio, with  $\Phi_R \approx$  the cellular RNA to protein ratio divided by 2.1 ([Dai et al., 2016](#)). (B) Experimental measurements of the cell doubling time  $\tau$  and cell cycle time  $t_{\text{cyc}}$  from [Si et al. \(2017\)](#). Dashed line shows fit to the data, which were used to estimate  $\langle \# \text{ori} \rangle$ .  $t_{\text{cyc}}$  was assumed to vary in proportion to  $\tau$  for doubling times greater than 40 minutes, and reach a minimum value of 73 minutes. See Appendix Estimation of  $\langle \# \text{ori} \rangle / \langle \# \text{ter} \rangle$  and  $\langle \# \text{ori} \rangle$  for additional details exact estimation of rRNA copy number. Red data points correspond to measurements in strain MG1655, while light green points are for strain NCM3722. Schematic shows the expected increase in replication forks (or number of ori regions) as *E. coli* cells grow faster.



**Figure 11–Figure supplement 1.** An interactive version of parts (B) and (C) of **Figure 11** which permit the user to modulate the rate of amino acid supply, the dissociation constant of amino acids to the ribosome, and the fraction of the ribosome pool that is actively translating. This interactive figure, and the code used to generate it, is available on the [paper website](#).